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(12) **United States Patent**
**Li et al.**

(10) **Patent No.: US 11,315,259 B2**
(45) **Date of Patent: Apr. 26, 2022**

(54) **EFFICIENT HUMAN POSE TRACKING IN VIDEOS**

(71) Applicant: **Snap Inc.**, Santa Monica, CA (US)

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(73) Assignee: **Snap Inc.**, Santa Monica, CA (US)

( * ) Notice: Subject to any disclaimer, the term of this patent is extended or adjusted under 35 U.S.C. 154(b) by 0 days.

(21) Appl. No.: **16/949,594**

(22) Filed: **Nov. 5, 2020**

(65) **Prior Publication Data**

US 2021/0125342 A1 Apr. 29, 2021

**Related U.S. Application Data**

(63) Continuation of application No. 16/206,684, filed on Nov. 30, 2018, now Pat. No. 10,861,170.

(51) **Int. Cl.**
***G06T 7/246*** (2017.01)
***G06T 7/73*** (2017.01)
(Continued)

(52) **U.S. Cl.**
CPC .......... ***G06T 7/246*** (2017.01); ***G06K 9/00744*** (2013.01); ***G06T 7/73*** (2017.01);
(Continued)

(58) **Field of Classification Search**
CPC .................................................. G06K 9/00744
See application file for complete search history.

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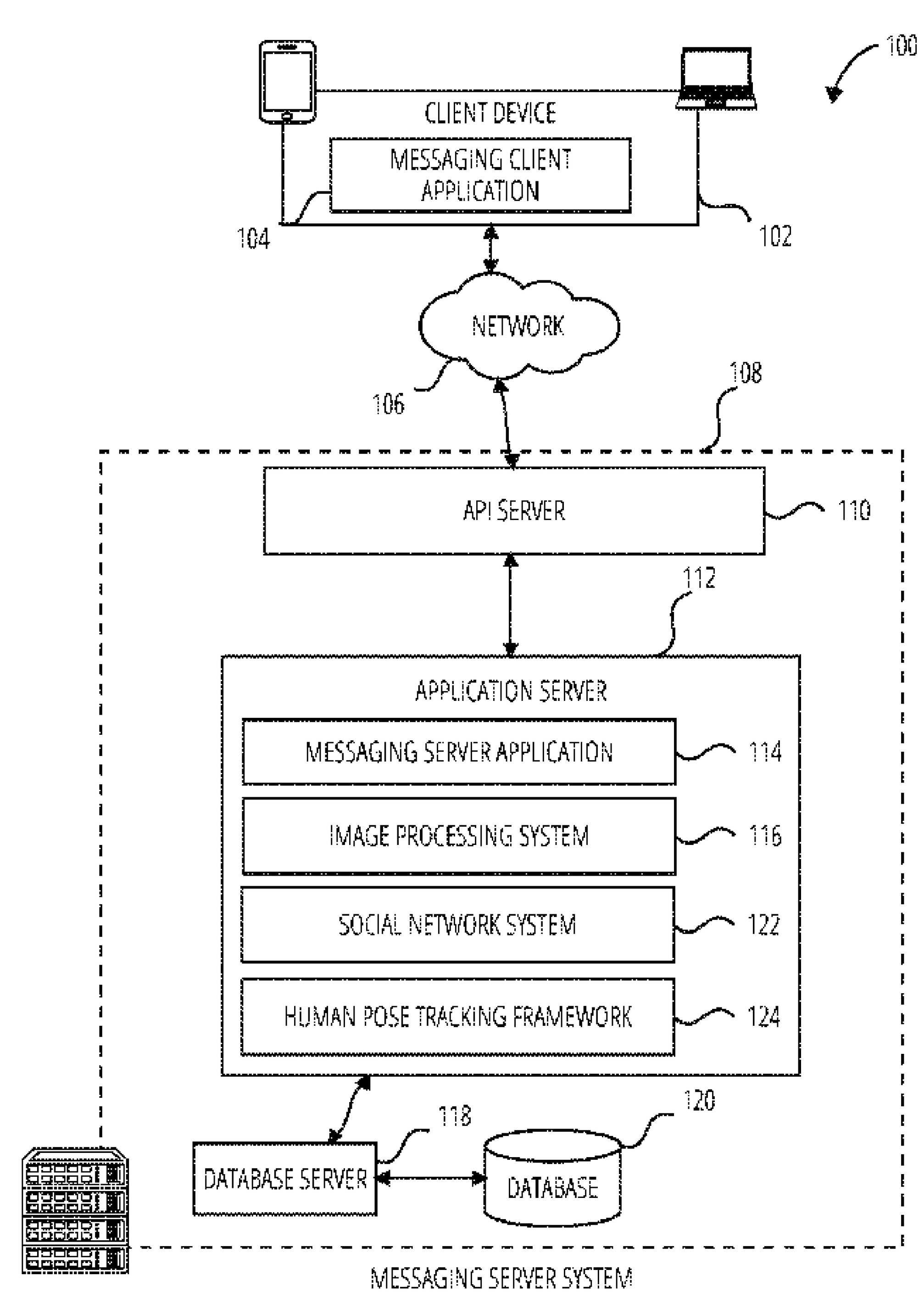
(Continued)

*Primary Examiner* — Edward Park
(74) *Attorney, Agent, or Firm* — Schwegman Lundberg & Woessner, P.A.

(57) **ABSTRACT**

Systems, devices, media and methods are presented for a human pose tracking framework. The human pose tracking framework may identify a message with video frames, generate, using a composite convolutional neural network, joint data representing joint locations of a human depicted in the video frames, the generating of the joint data by the composite convolutional neural network done by a deep convolutional neural network operating on one portion of the video frames, a shallow convolutional neural network operating on a another portion of the video frames, and tracking the joint locations using a one-shot learner neural network that is trained to track the joint locations based on a concatenation of feature maps and a convolutional pose machine. The human pose tracking framework may store, the joint locations, and cause presentation of a rendition of the joint locations on a user interface of a client device.

**20 Claims, 14 Drawing Sheets**



(51) **Int. Cl.**

| | |
|---|---|
| ***G06K 9/00*** | (2022.01) |
| *H04L 67/01* | (2022.01) |
| *G06F 3/04817* | (2022.01) |
| *H04L 51/04* | (2022.01) |

(52) **U.S. Cl.**

CPC ...... *G06F 3/04817* (2013.01); *G06T 2200/24* (2013.01); *G06T 2207/10016* (2013.01); *G06T 2207/20081* (2013.01); *G06T 2207/20084* (2013.01); *G06T 2207/30196* (2013.01); *H04L 51/04* (2013.01); *H04L 67/42* (2013.01)

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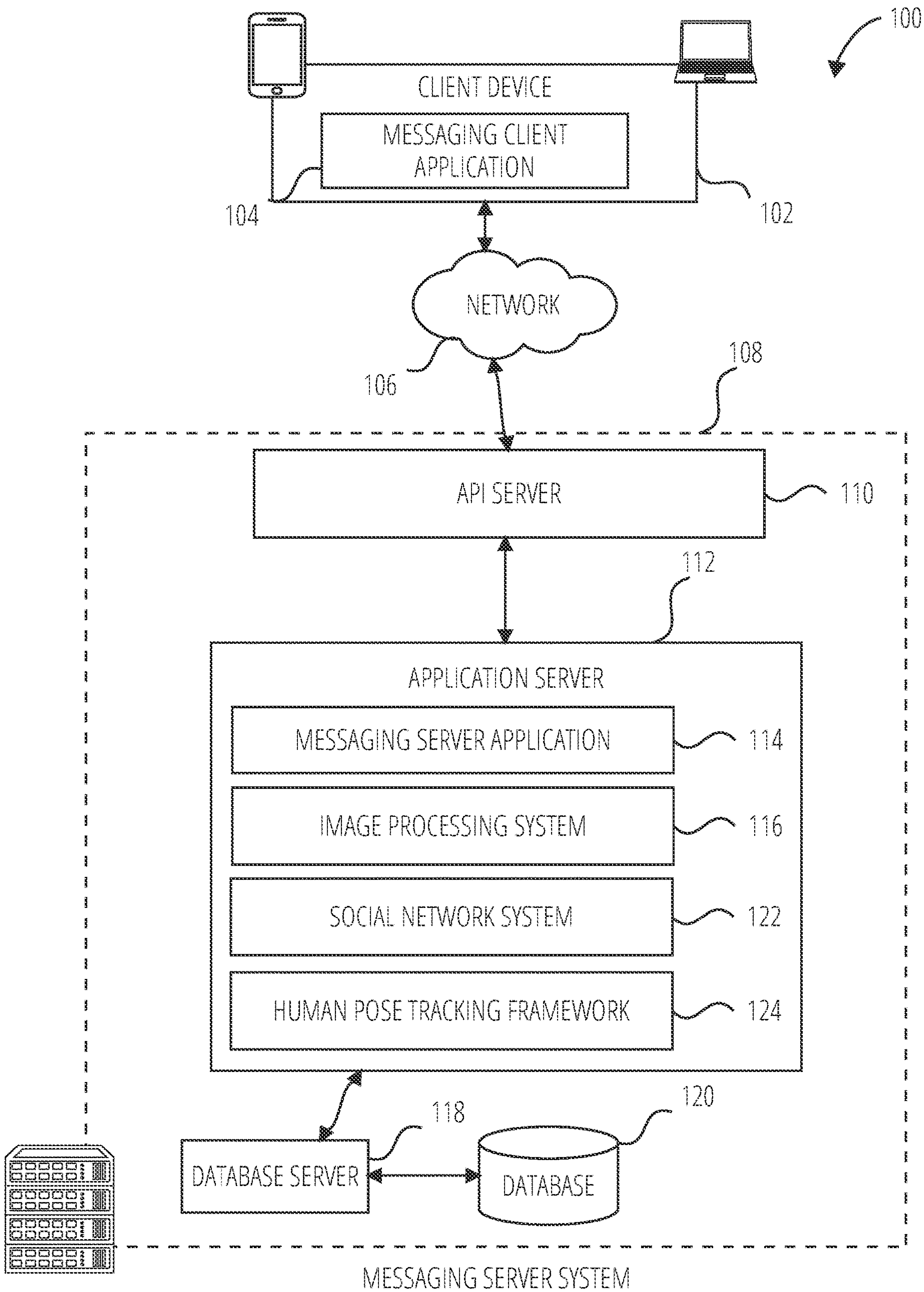
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CLIENT DEVICE
MESSAGING CLIENT APPLICATION
104
102
NETWORK
106
108
API SERVER
110
112
APPLICATION SERVER
MESSAGING SERVER APPLICATION
114
IMAGE PROCESSING SYSTEM
116
SOCIAL NETWORK SYSTEM
122
HUMAN POSE TRACKING FRAMEWORK
124
118
120
DATABASE SERVER
DATABASE
MESSAGING SERVER SYSTEM

FIG. 1

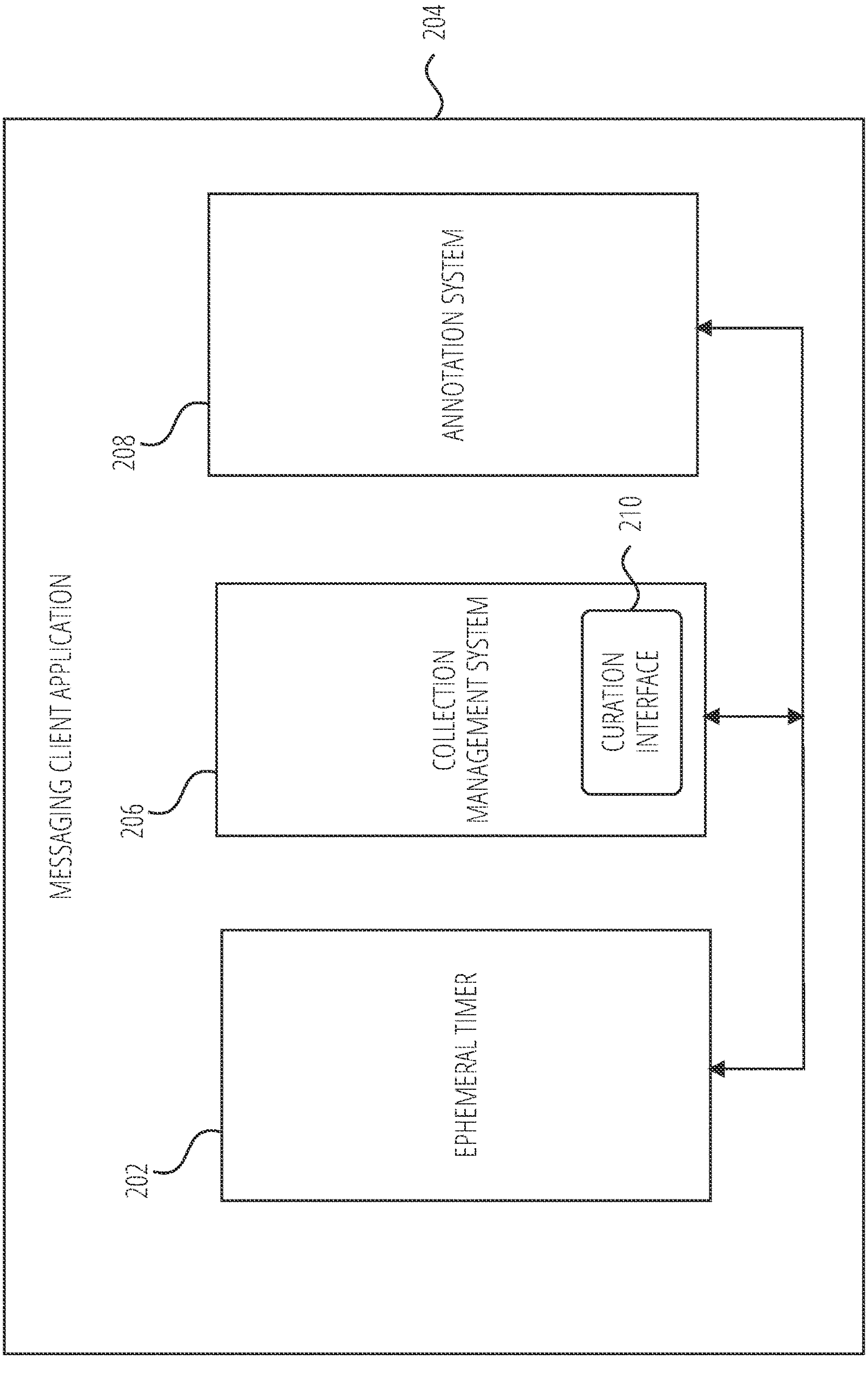

204
MESSAGING CLIENT APPLICATION
208
ANNOTATION SYSTEM
210
206
COLLECTION MANAGEMENT SYSTEM
CURATION INTERFACE
202
EPHEMERAL TIMER

FIG. 2

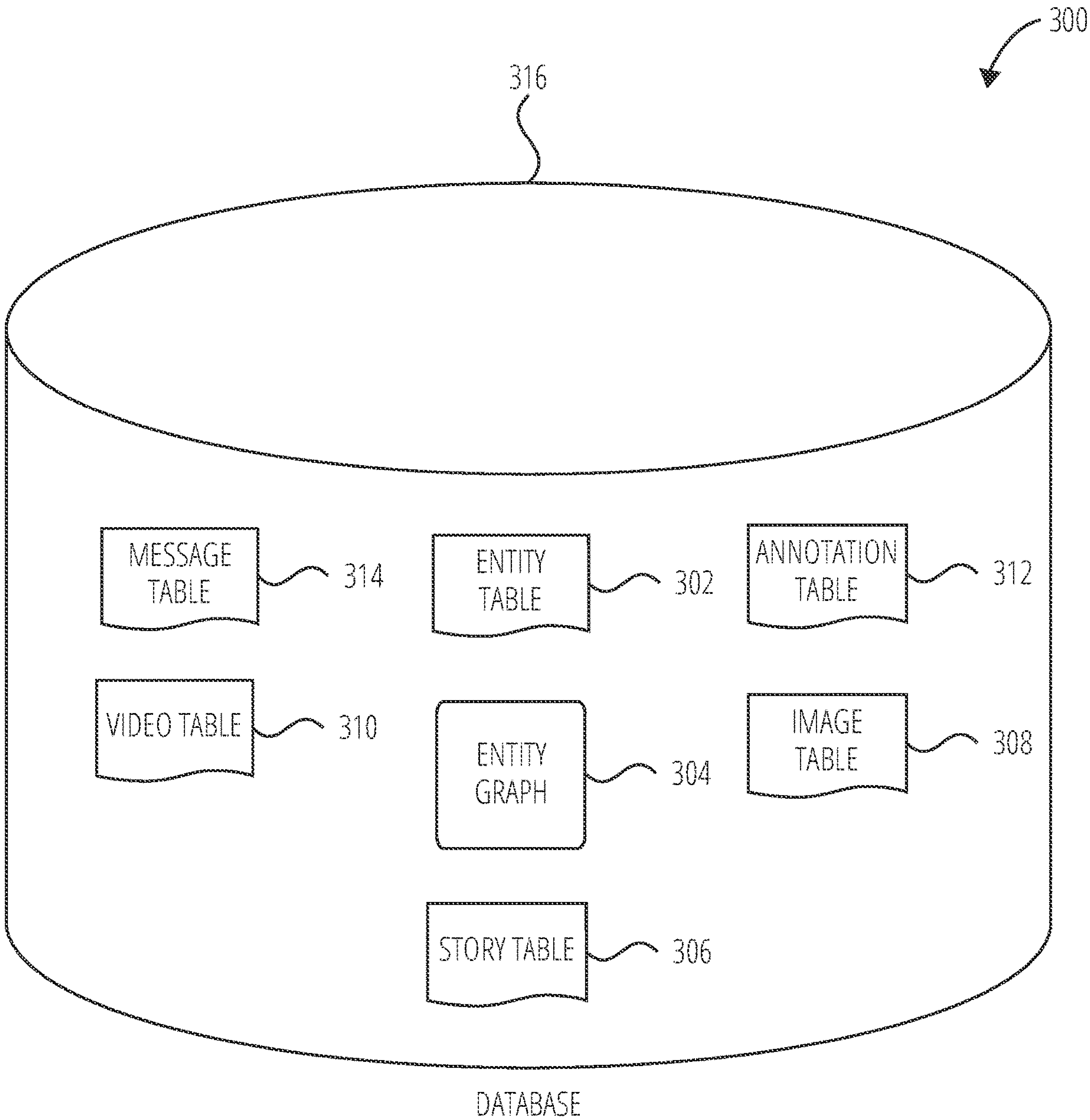

300
316
MESSAGE TABLE
314
ENTITY TABLE
302
ANNOTATION TABLE
312
VIDEO TABLE
310
ENTITY GRAPH
304
IMAGE TABLE
308
STORY TABLE
306
DATABASE

FIG. 3

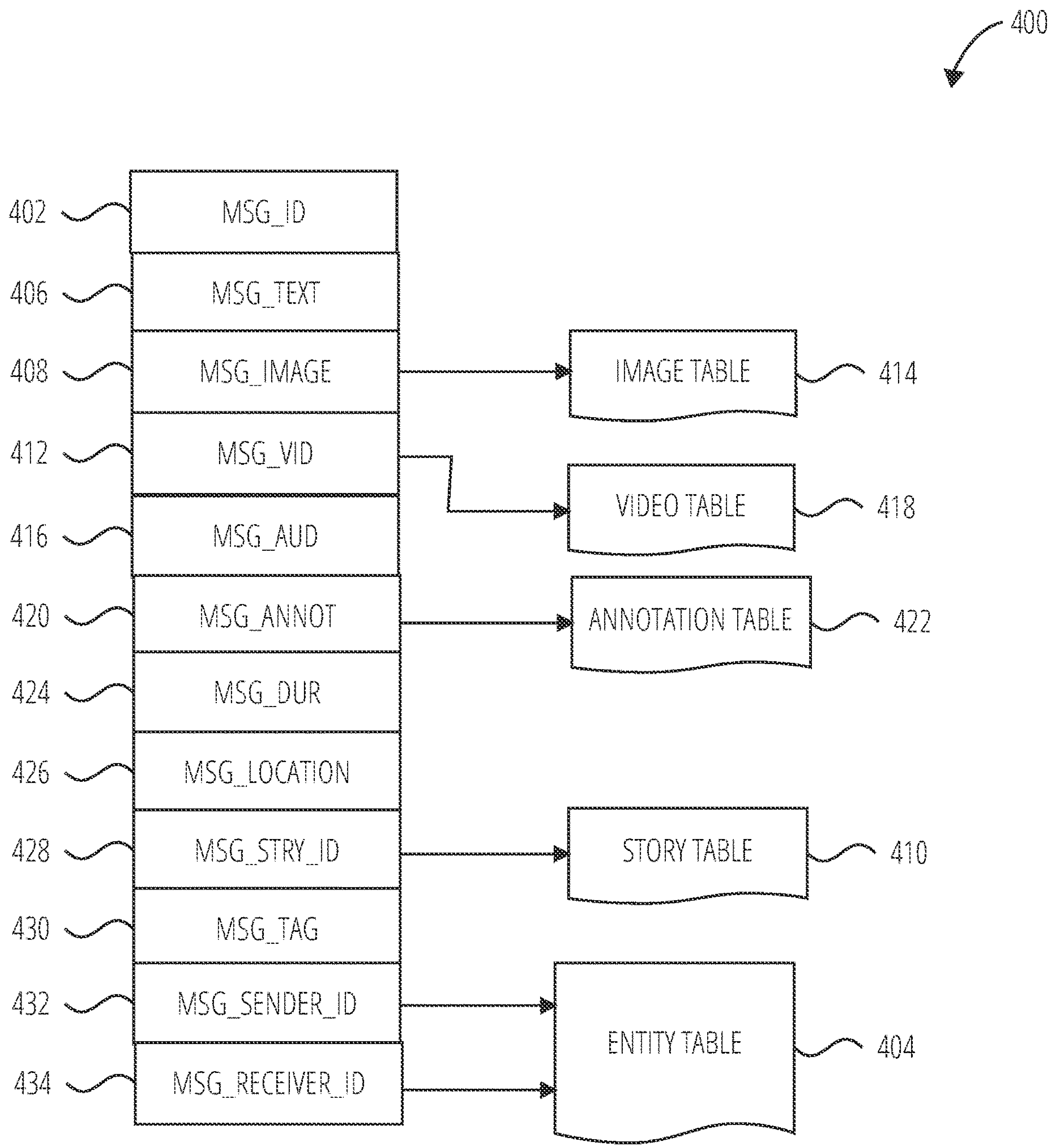

400
402
MSG_ID
406
MSG_TEXT
408
MSG_IMAGE
IMAGE TABLE
414
412
MSG_VID
VIDEO TABLE
418
416
MSG_AUD
420
MSG_ANNOT
ANNOTATION TABLE
422
424
MSG_DUR
426
MSG_LOCATION
428
MSG_STRY_ID
STORY TABLE
410
430
MSG_TAG
432
MSG_SENDER_ID
434
MSG_RECEIVER_ID
ENTITY TABLE
404

FIG. 4

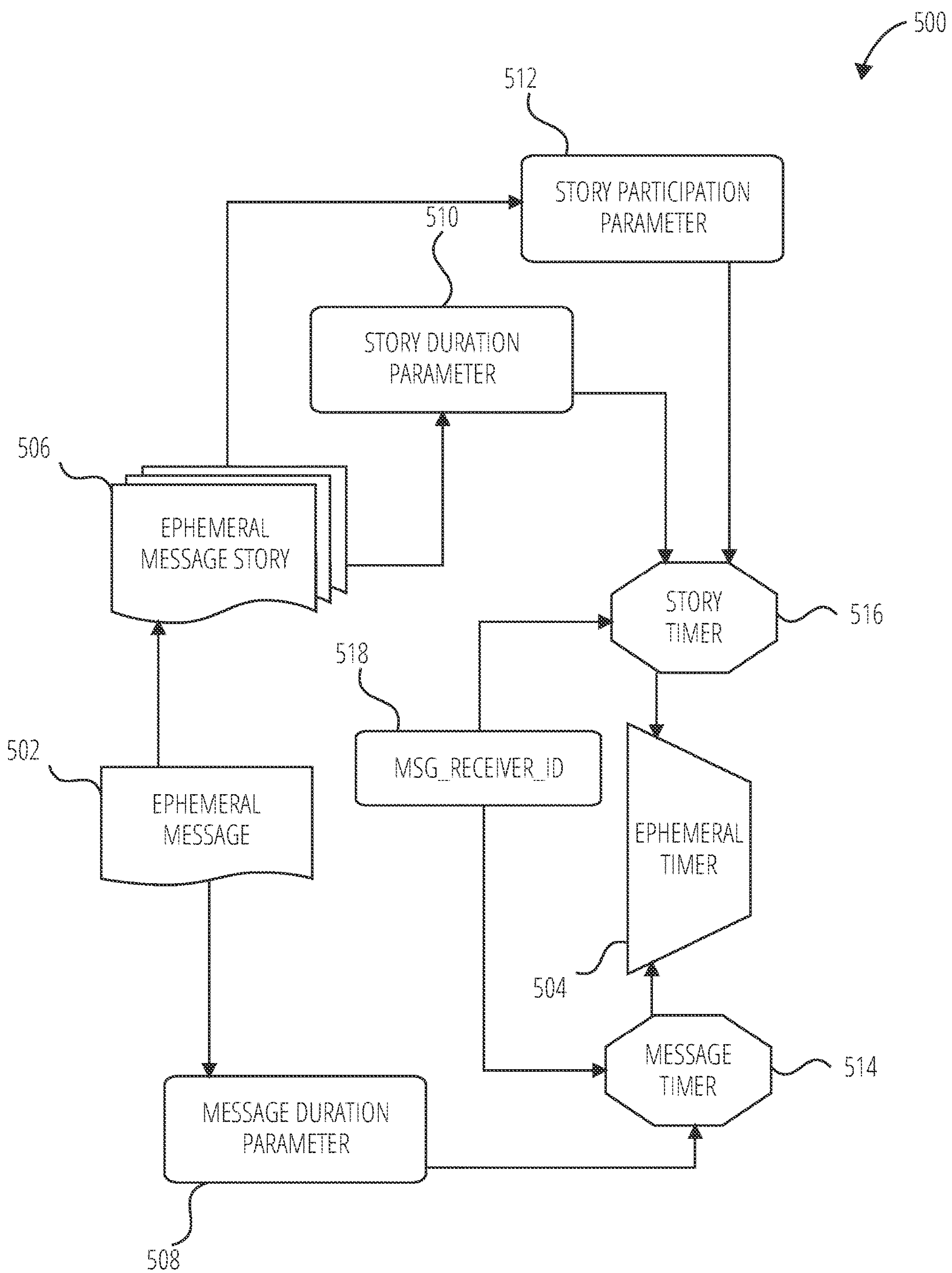
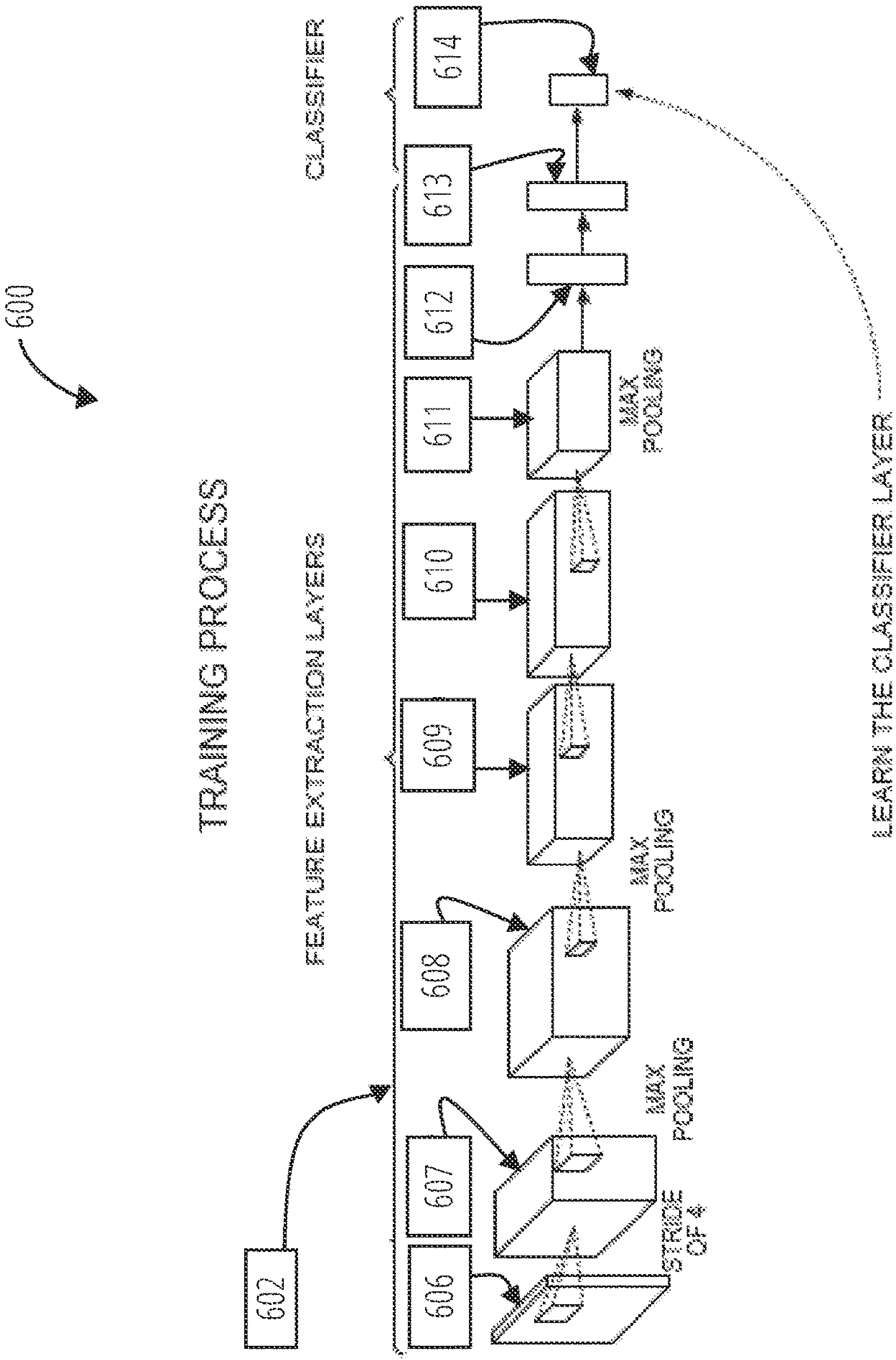

500
512
STORY PARTICIPATION PARAMETER
510
STORY DURATION PARAMETER
506
EPHEMERAL MESSAGE STORY
STORY TIMER
516
518
MSG_RECEIVER_ID
502
EPHEMERAL MESSAGE
EPHEMERAL TIMER
504
MESSAGE TIMER
514
MESSAGE DURATION PARAMETER
508

FIG. 5



600
TRAINING PROCESS
FEATURE EXTRACTION LAYERS
CLASSIFIER
602
606
607
608
609
610
611
612
613
614
STRIDE OF 4
MAX POOLING
MAX POOLING
MAX POOLING
LEARN THE CLASSIFIER LAYER


FIG. 6

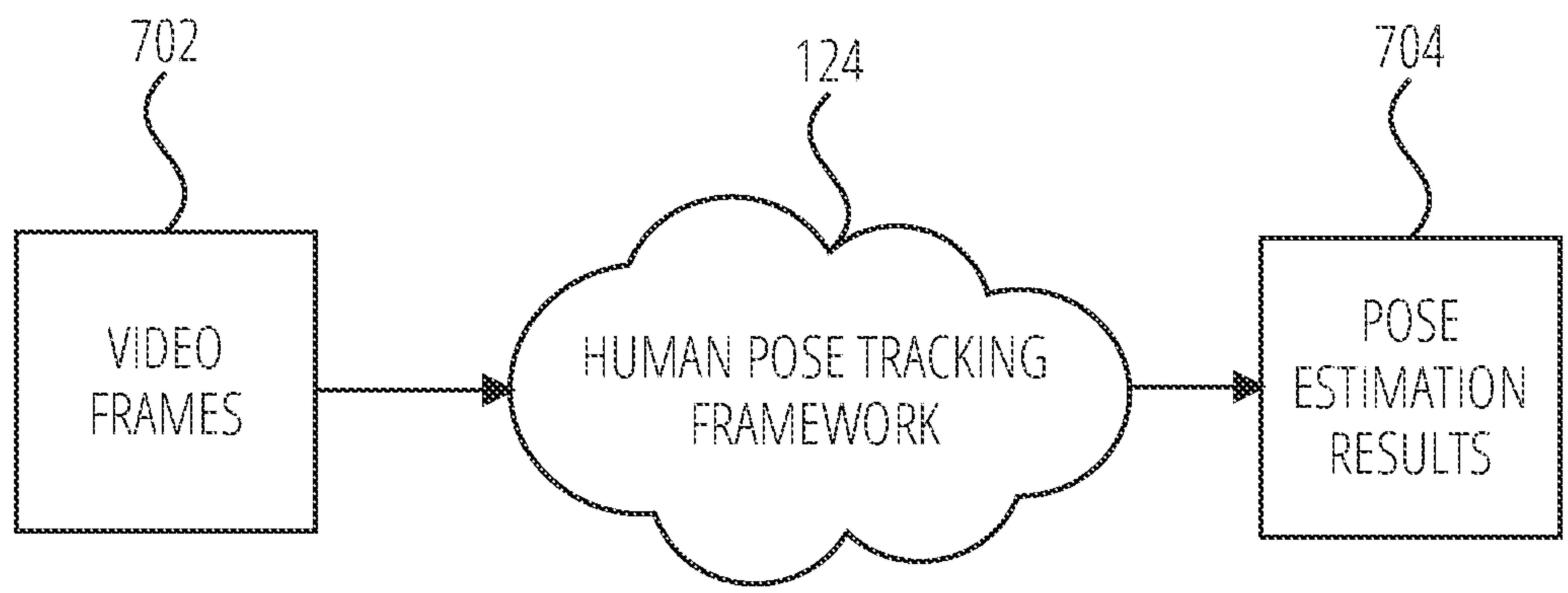

702
124
704
VIDEO FRAMES
HUMAN POSE TRACKING FRAMEWORK
POSE ESTIMATION RESULTS

FIG. 7

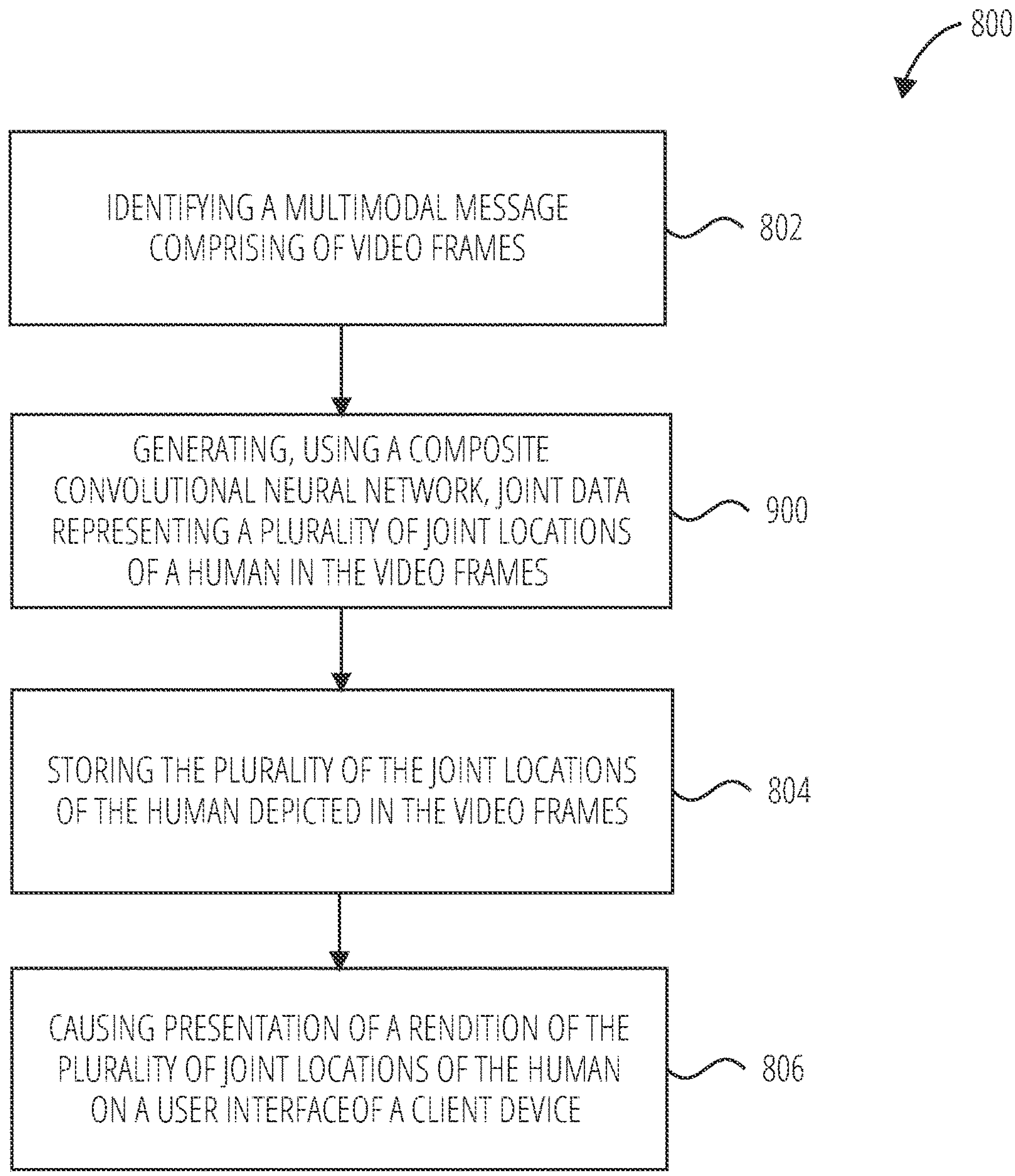

800
IDENTIFYING A MULTIMODAL MESSAGE COMPRISING OF VIDEO FRAMES
802
GENERATING, USING A COMPOSITE CONVOLUTIONAL NEURAL NETWORK, JOINT DATA REPRESENTING A PLURALITY OF JOINT LOCATIONS OF A HUMAN IN THE VIDEO FRAMES
900
STORING THE PLURALITY OF THE JOINT LOCATIONS OF THE HUMAN DEPICTED IN THE VIDEO FRAMES
804
CAUSING PRESENTATION OF A RENDITION OF THE PLURALITY OF JOINT LOCATIONS OF THE HUMAN ON A USER INTERFACEOF A CLIENT DEVICE
806

FIG. 8

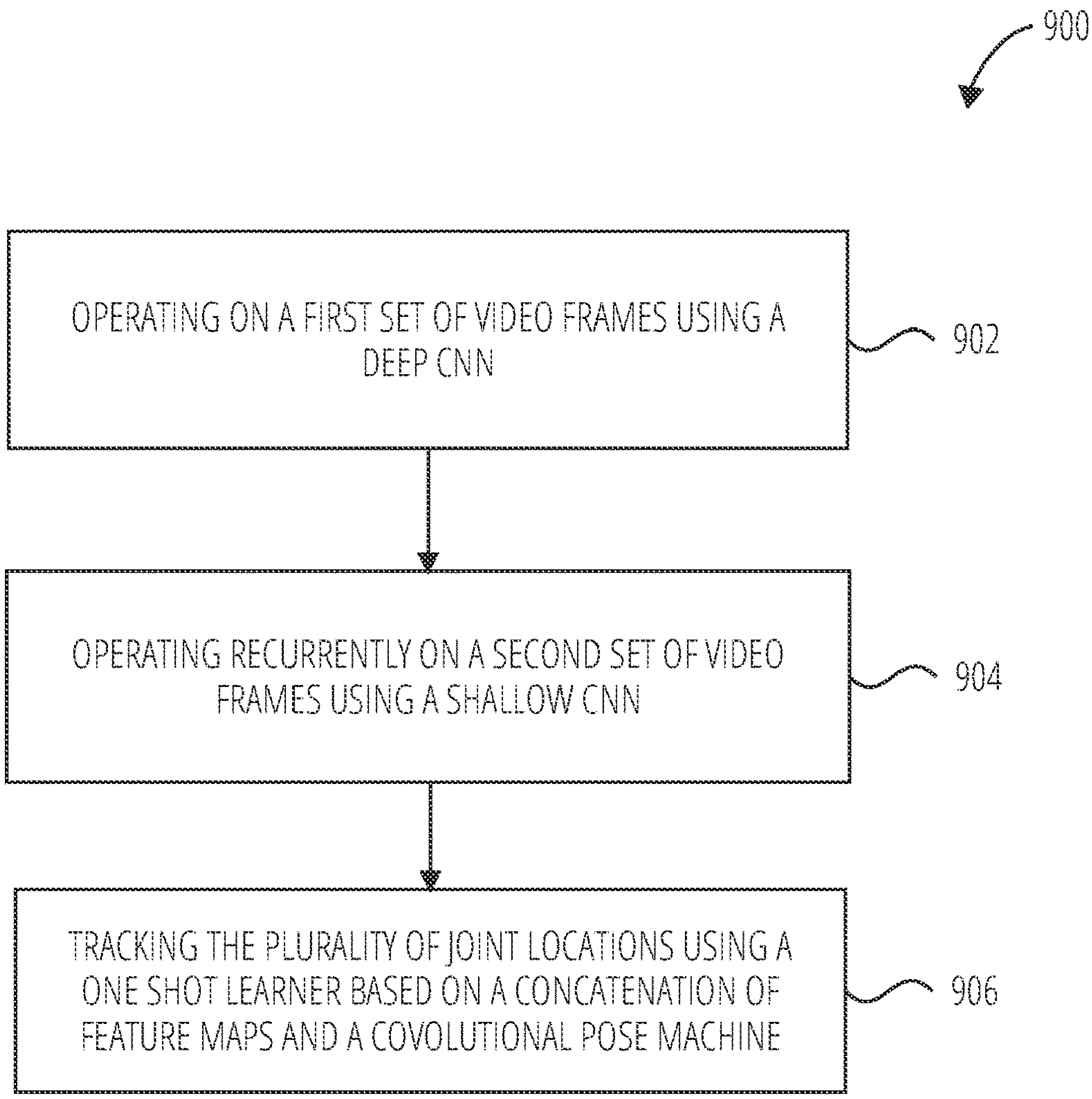

900
OPERATING ON A FIRST SET OF VIDEO FRAMES USING A DEEP CNN
902
OPERATING RECURRENTLY ON A SECOND SET OF VIDEO FRAMES USING A SHALLOW CNN
904
TRACKING THE PLURALITY OF JOINT LOCATIONS USING A ONE SHOT LEARNER BASED ON A CONCATENATION OF FEATURE MAPS AND A COVOLUTIONAL POSE MACHINE
906

FIG. 9

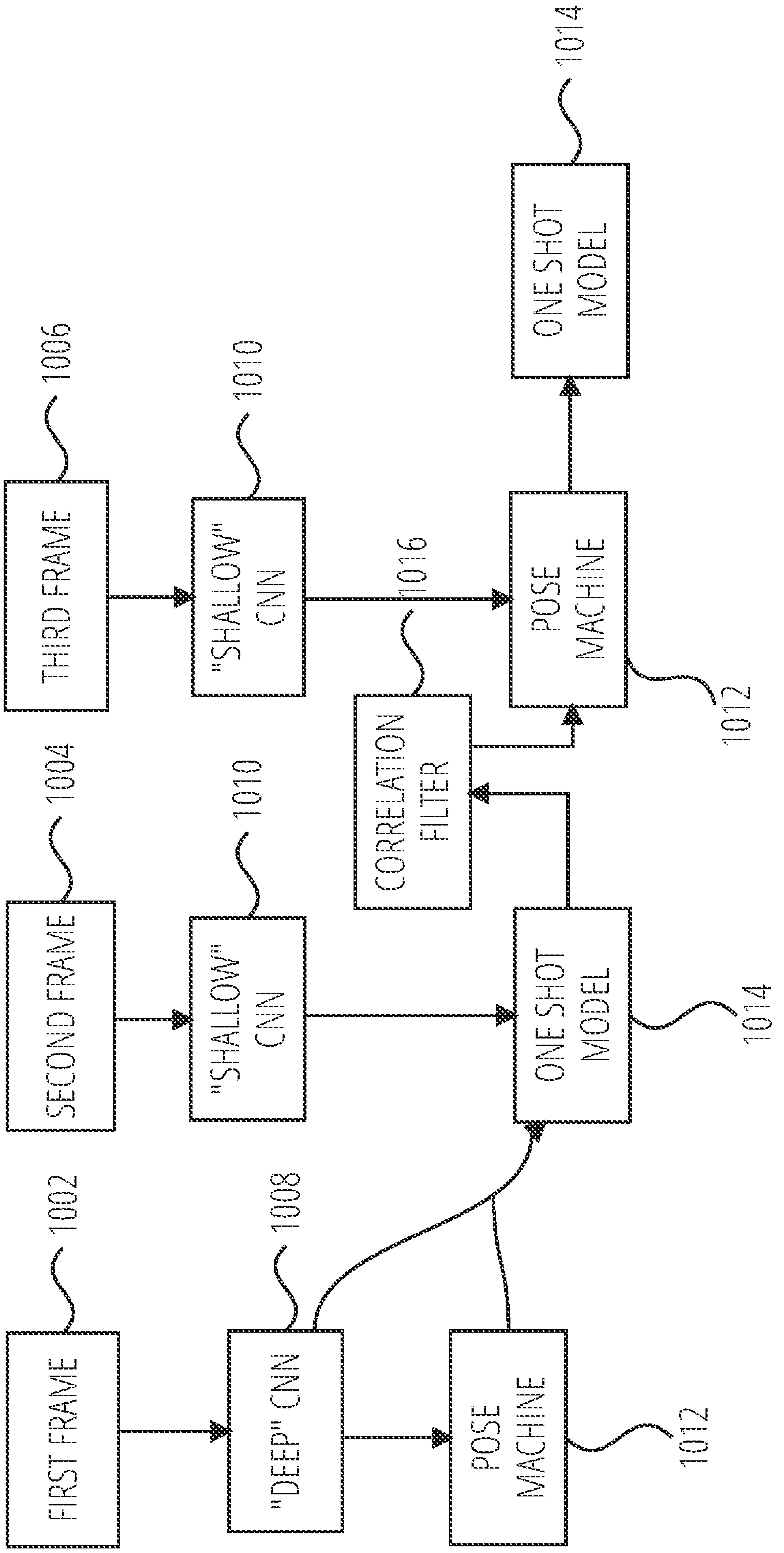

FIRST FRAME
1002
SECOND FRAME
1004
THIRD FRAME
1006
"DEEP" CNN
1008
"SHALLOW" CNN
1010
"SHALLOW" CNN
1010
POSE MACHINE
1012
ONE SHOT MODEL
1014
CORRELATION FILTER
1016
POSE MACHINE
1012
ONE SHOT MODEL
1014

FIG. 10

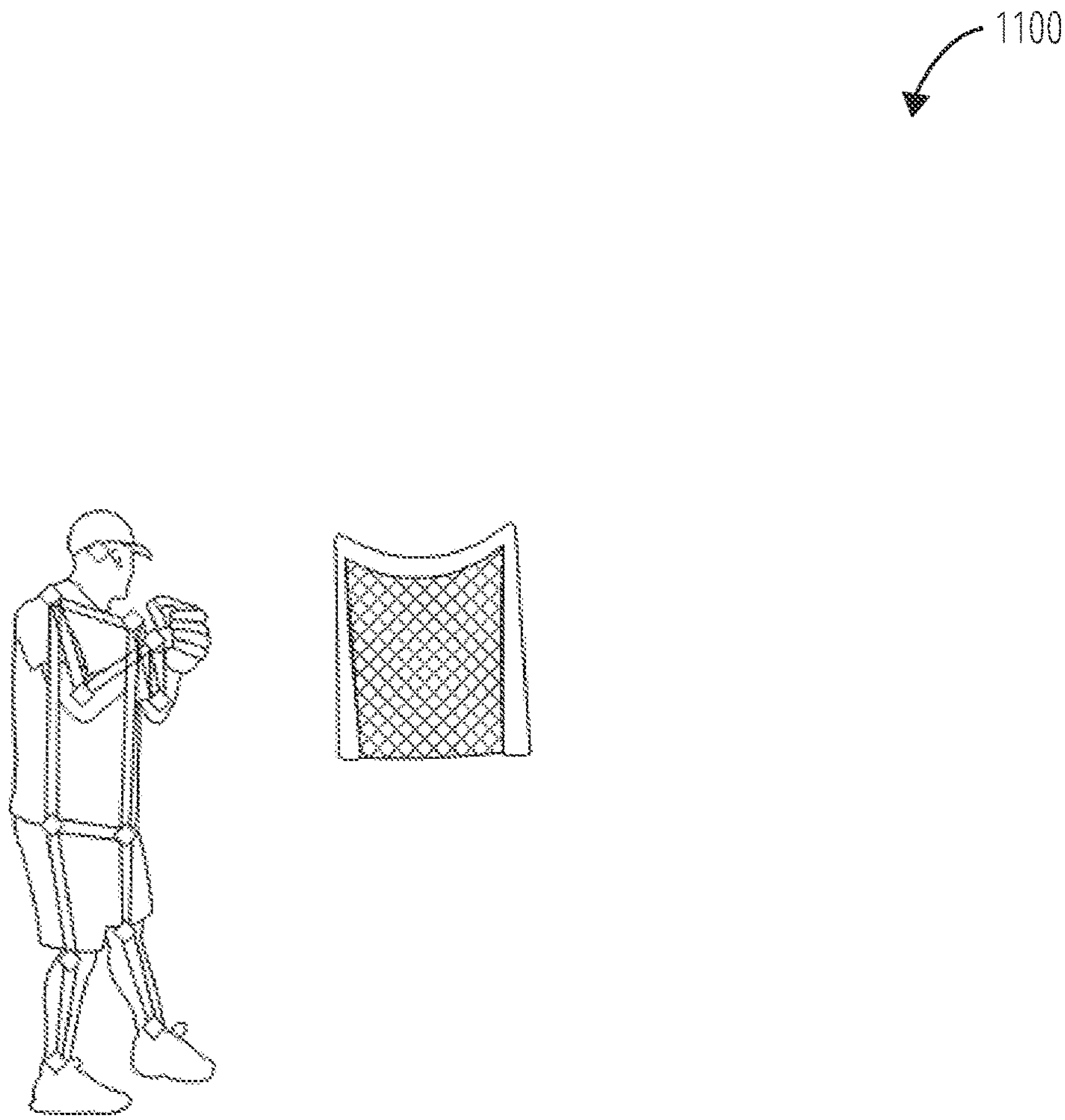



FIG. 11

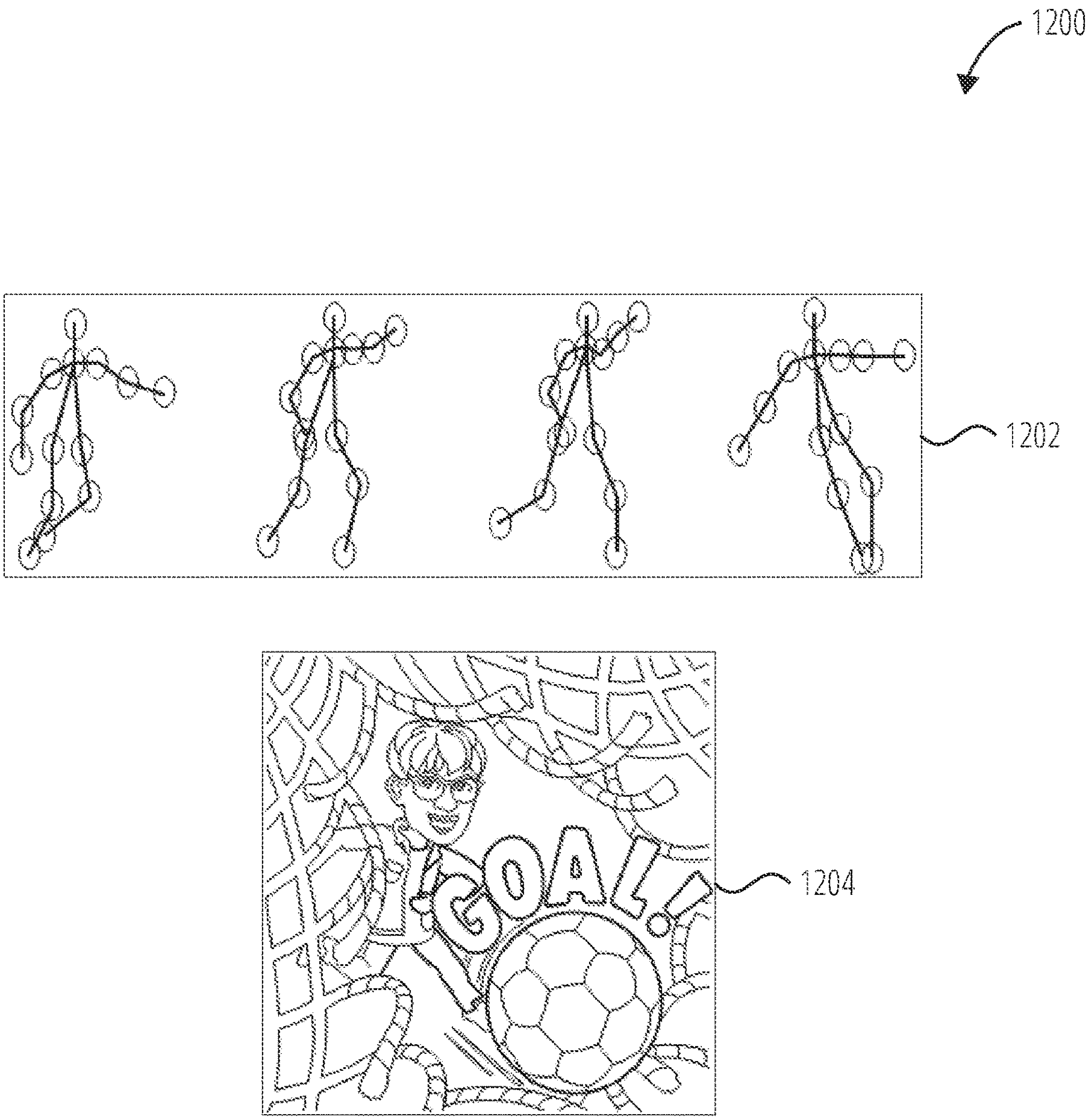
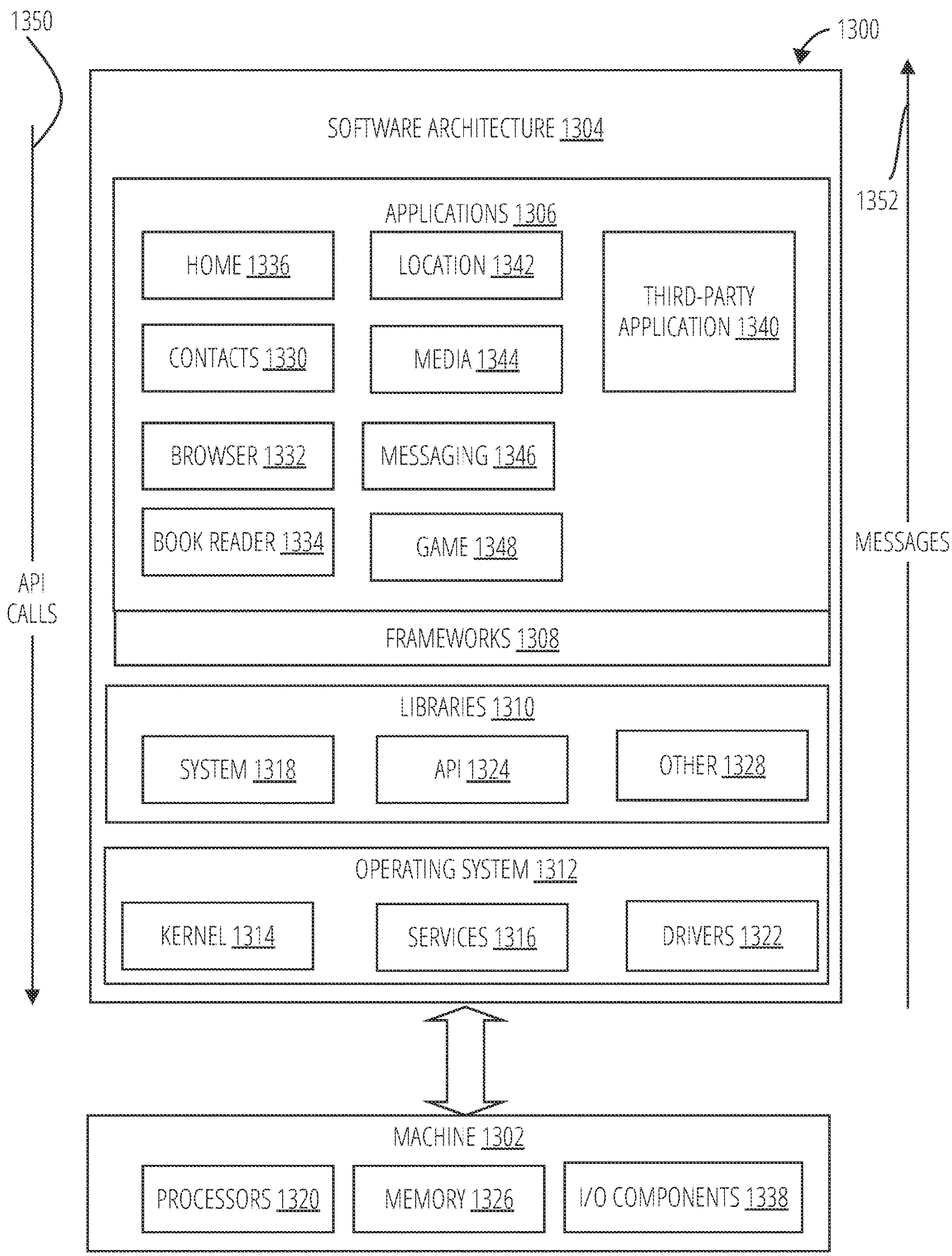



FIG. 12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LOCATION 1342
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MEDIA 1344
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BOOK READER 1334
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API 1324
OTHER 1328
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KERNEL 1314
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API CALLS
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MESSAGES
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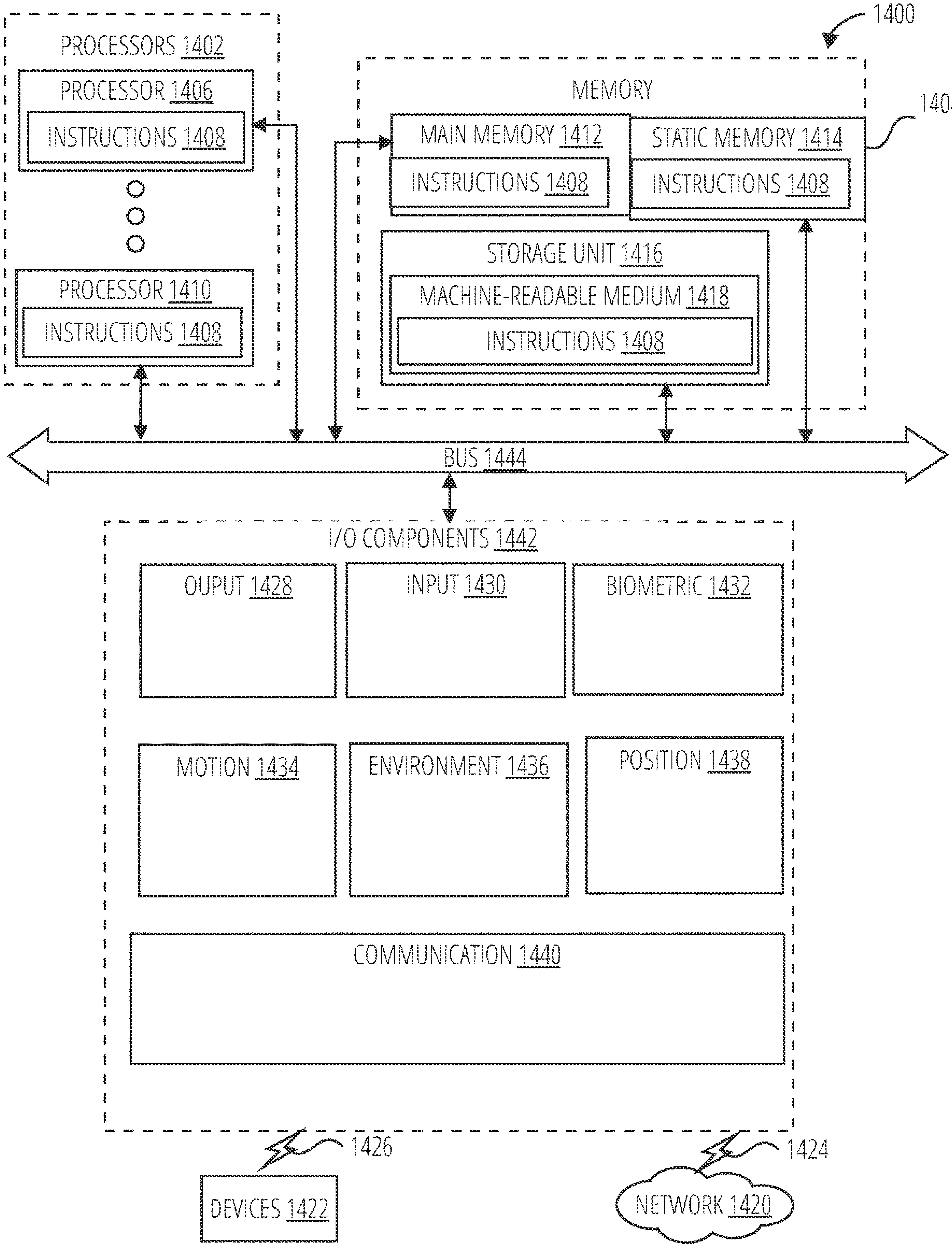
PROCESSORS 1320
MEMORY 1326
I/O COMPONENTS 1338

FIG. 13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MEMORY
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STATIC MEMORY 1414
INSTRUCTIONS 1408
STORAGE UNIT 1416
MACHINE-READABLE MEDIUM 1418
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I/O COMPONENTS 1442
OUPUT 1428
INPUT 1430
BIOMETRIC 1432
MOTION 1434
ENVIRONMENT 1436
POSITION 1438
COMMUNICATION 1440
1426
1424
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FIG. 14

# EFFICIENT HUMAN POSE TRACKING IN VIDEOS

## CLAIM OF PRIORITY

This application is a continuation of U.S. patent application Ser. No. 16/206,684, filed on Nov. 30, 2018, which is incorporated herein by reference in its entirety.

## TECHNICAL FIELD

Embodiments of the present disclosure relate generally to human pose tracking in videos using convolutional neural networks.

## BACKGROUND

A neural network, sometimes referred to as an artificial neural network, is a computing system based on the consideration of biological neural networks of animal brains. Such systems progressively improve performance, which is referred to as learning, to perform tasks, typically without task-specific programming. For example, in image recognition, a neural network may be taught to identify images that contain an object by analyzing example images that have been tagged with a name for the object and, having learned the object and name, may use the analytic results to identify the object in untagged images. A neural network is based on a collection of connected units called neurons, where each connection, called a synapse, between neurons can transmit a unidirectional signal with an activating strength that varies with the strength of the connection. The receiving neuron can activate and propagate a signal to downstream neurons connected to it, typically based on whether the combined incoming signals, which are from potentially many transmitting neurons, are of sufficient strength, where strength is a parameter.

A long short-term memory (LSTM) serving as a neuron includes several gates to handle input vectors (e.g., phonemes from an utterance), a memory cell, and an output vector (e.g., contextual representation). The input gate and output gate control the information flowing into and out of the memory cell, respectively, whereas forget gates optionally remove information from the memory cell based on the inputs from linked cells earlier in the neural network. Weights and bias vectors for the various gates are adjusted over the course of a training phase, and once the training phase is complete, those weights and biases are finalized for normal operation. One of skill in the art will appreciate that neurons and neural networks may be constructed programmatically (e.g., via software instructions) or via specialized hardware linking each neuron to form the neural network.

Neural networks use "features" for analyzing the data to generate assessments (e.g., recognize units of speech). A feature is an individual measurable property of a phenomenon being observed. The concept of feature is related to that of an explanatory variable used in statistical techniques such as linear regression. Further, deep features represent the output of nodes in hidden layers of the deep neural network.

## BRIEF DESCRIPTION OF THE DRAWINGS

To easily identify the discussion of any particular element or act, the most significant digit or digits in a reference number refer to the figure number in which that element is first introduced.

FIG. **1** is a block diagram showing an example messaging system for exchanging data (e.g., messages and associated content) over a network.

FIG. **2** is block diagram illustrating further details regarding a messaging system, according to example embodiments.

FIG. **3** is a schematic diagram illustrating data which may be stored in the database of the messaging server system, according to certain example embodiments.

FIG. **4** is a schematic diagram illustrating a structure of a message, according to some embodiments, generated by a messaging client application for communication.

FIG. **5** is a schematic diagram illustrating an example access-limiting process, in terms of which access to content (e.g., an ephemeral message, and associated multimedia payload of data) or a content collection (e.g., an ephemeral message story) may be time-limited (e.g., made ephemeral).

FIG. **6** is a diagrammatic illustration of a feature-extraction process and classifier training, according to some example embodiments.

FIG. **7** is a block diagram illustrating a human pose tracking framework, according to some example embodiments.

FIG. **8** is a flow diagram illustrating a human pose tracking framework, according to some example embodiments.

FIG. **9** is a flow diagram illustrating a human pose tracking framework, according to some example embodiments.

FIG. **10** is a diagrammatic illustration of a human pose tracking system according to an example embodiment.

FIG. **11** is a diagrammatic illustration of joint localization according to an example embodiment.

FIG. **12** is a diagrammatic illustration of graphical data, according to an example embodiment.

FIG. **13** is a block diagram showing a software architecture within which the present disclosure may be implemented, in accordance with some example embodiments.

FIG. **14** is a diagrammatic representation of a machine in the form of a computer system within which a set of instructions may be executed for causing the machine to perform any one or more of the methodologies discussed herein, in accordance with some example embodiments.

## DETAILED DESCRIPTION

Human pose tracking aims to track articulated body joints in monocular videos. Human pose tracking in videos poses a challenging problem because of appearance changes, large pose deformations, occlusions and other complex interactions between humans and objects. Leveraging temporal information across video frames can improve the consistency and efficiency of the human pose tracking problem. Described in detail below is a composite convolutional neural network model, according to some example embodiments, that is trained to exploit temporal information across video frames in order to improve efficiency and accuracy in human pose tracking.

FIG. **1** is a block diagram showing an example messaging system **100** for exchanging data (e.g., messages and associated content) over a network. The messaging system **100** includes multiple client devices **102**, each of which hosts several applications including a messaging client application **104**. Each messaging client application **104** is communicatively coupled to other instances of the messaging client application **104** and a messaging server system **108** via a network **106** (e.g., the Internet).

Accordingly, each messaging client application **104** can communicate and exchange data with another messaging client application **104** and with the messaging server system **108** via the network **106**. The data exchanged between messaging client applications **104**, and between a messaging client application **104** and the messaging server system **108**, includes functions (e.g., commands to invoke functions) as well as payload data (e.g., text, audio, video or other multimedia data).

The messaging server system **108** provides server-side functionality via the network **106** to a particular messaging client application **104**. While certain functions of the messaging system **100** are described herein as being performed by either a messaging client application **104** or by the messaging server system **108**, it will be appreciated that the location of certain functionality either within the messaging client application **104** or the messaging server system **108** is a design choice. For example, it may be technically preferable to initially deploy certain technology and functionality within the messaging server system **108**, but to later migrate this technology and functionality to the messaging client application **104** where a client device **102** has a sufficient processing capacity.

The messaging server system **108** supports various services and operations that are provided to the messaging client application **104**. Such operations include transmitting data to, receiving data from, and processing data generated by the messaging client application **104**. This data may include, message content, client device information, geolocation information, media annotation and overlays, message content persistence conditions, social network information, and live event information, as examples. Data exchanges within the messaging system **100** are invoked and controlled through functions available via user interfaces (UIs) of the messaging client application **104**.

Turning now specifically to the messaging server system **108**, an Application Program Interface (API) server **110** is coupled to, and provides a programmatic interface to, an application server **112**. The application server **112** is communicatively coupled to a database server **118**, which facilitates access to a database **120** in which is stored data associated with messages processed by the application server **112**.

Dealing specifically with the Application Program Interface (API) server **110**, this server receives and transmits message data (e.g., commands and message payloads) between the client device **102** and the application server **112**. Specifically, the Application Program Interface (API) server **110** provides a set of interfaces (e.g., routines and protocols) that can be called or queried by the messaging client application **104** in order to invoke functionality of the application server **112**. The Application Program Interface (API) server **110** exposes various functions supported by the application server **112**, including account registration, login functionality, the sending of messages, via the application server **112**, from a particular messaging client application **104** to another messaging client application **104**, the sending of media tiles (e.g., images or video) from a messaging client application **104** to the messaging server application **114**, and for possible access by another messaging client application **104**, the setting of a collection of media data (e.g., story), the retrieval of a list of friends of a user of a client device **102**, the retrieval of such collections, the retrieval of messages and content, the adding and deletion of friends to a social graph, the location of friends within a social graph, opening an application event (e.g., relating to the messaging client application **104**).

The application server **112** hosts a number of applications and subsystems, including a messaging server application **114**, an image processing system **116** and a social network system **122**. The messaging server application **114** implements a number of message processing technologies and functions, particularly related to the aggregation and other processing of content (e.g., textual and multimedia content) included in messages received from multiple instances of the messaging client application **104**. As will be described in further detail, the text and media content from multiple sources may be aggregated into collections of content (e.g., called stories or galleries). These collections are then made available, by the messaging server application **114**, to the messaging client application **104**. Other processor and memory intensive processing of data may also be performed server-side by the messaging server application **114**, in view of the hardware requirements for such processing.

The application server **112** also includes an image processing system **116** that is dedicated to performing various image processing operations, typically with respect to images or video received within the payload of a message at the messaging server application **114**.

The social network system **122** supports various social networking functions and services and makes these functions and services available to the messaging server application **114**. To this end, the social network system **122** maintains and accesses an entity graph **304** within the database **120**. Examples of functions and services supported by the social network system **122** include the identification of other users of the messaging system **100** with which a particular user has relationships or is "following", and also the identification of other entities and interests of a particular user.

The human pose tracking framework **124** may be integrated within an application server **112**. The human pose tracking framework **124** may be coupled with a messaging server application, **114**, image processing system **116** and a social network system **122**. The human pose tracking framework **124** may use video data captured by a camera component of a client device **102**. The human pose tracking framework **124** may transmit data to the messaging client application **104** via the network **106**. Further detail regarding the human pose tracking framework **124** will be discussed below. The application server **112** is communicatively coupled to a database server **118**, which facilitates access to a database **120** in which is stored data associated with messages processed by the messaging server application **114**.

FIG. **2** is block diagram illustrating further details regarding the messaging system, **100**, according to example embodiments. Specifically, the messaging system **100** is shown to comprise a messaging client application **204** and the application server **112**, which in turn embody a number of some subsystems, namely an ephemeral timer system **202**, a collection management system **206** and an annotation system **208**.

The ephemeral timer system **202** is responsible for enforcing the temporary access to content permitted by the messaging client application **204** and the messaging server application **114**. To this end, the ephemeral timer system **202** incorporates multiple timers that, based on duration and display parameters associated with a message, or collection of messages (e.g., a story), selectively display and enable access to messages and associated content via the messaging client application **204**. Further details regarding the operation of the ephemeral timer system **202** are provided below.

The collection management system **206** is responsible for managing collections of media (e.g., collections of text, image video and audio data). In some examples, a collection of content (e.g., messages, including images, video, text and audio) may be organized into an "event gallery" or an "event story." Such a collection may be made available for a specified time period, such as the duration of an event to which the content relates. For example, content relating to a music concert may be made available as a "story" for the duration of that music concert. The collection management system **206** may also be responsible for publishing an icon that provides notification of the existence of a particular collection to the user interface of the messaging client application **204**.

The collection management system **206** furthermore includes a curation interface **210** that allows a collection manager to manage and curate a particular collection of content. For example, the curation interface **210** enables an event organizer to curate a collection of content relating to a specific event (e.g., delete inappropriate content or redundant messages). Additionally, the collection management system **206** employs machine vision (or image recognition technology) and content rules to automatically curate a content collection. In certain embodiments, compensation may be paid to a user for inclusion of user-generated content into a collection. In such cases, the curation interface **210** operates to automatically make payments to such users for the use of their content.

The annotation system **208** provides various functions that enable a user to annotate or otherwise modify or edit media content associated with a message. For example, the annotation system **208** provides functions related to the generation and publishing of media overlays for messages processed by the messaging system **100**. The annotation system **208** operatively supplies a media overlay, modification, enhancement or effect (e.g., a filter) to the messaging client application **204** based on a geolocation of the client device **102**. In another example, the annotation system **208** operatively supplies a media overlay to the messaging client application **204** based on other information, such as, social network information of the user of the client device **102**. A media overlay may include audio and visual content and visual effects. Examples of audio and visual content include pictures, texts, logos, animations, and sound effects. An example of a visual effect includes color overlaying. The audio and visual content or the visual effects can be applied to a media content item (e.g., a photo) at the client device **102**. For example, the media overlay includes text that can be overlaid on top of a photograph taken by the client device **102**. In another example, the media overlay includes an identification of a location overlay (e.g., Venice beach), a name of a live event, or a name of a merchant overlay (e.g., Beach Coffee House). In another example, the annotation system **208** uses the geolocation of the client device **102** to identify a media overlay that includes the name of a merchant at the geolocation of the client device **102**. The media overlay may include other indicia associated with the merchant. The media overlays may be stored in the database **120** and accessed through the database server **118**.

In one example embodiment, the annotation system **208** provides a user-based publication platform that enables users to select a geolocation on a map, and upload content associated with the selected geolocation. The user may also specify circumstances under which a particular media overlay should be offered to other users. The annotation system **208** generates a media overlay that includes the uploaded content and associates the uploaded content with the selected geolocation.

In another example embodiment, the annotation system **208** provides a merchant-based publication platform that enables merchants to select a particular media overlay associated with a geolocation via a bidding process. For example, the annotation system **208** associates the media overlay of a highest bidding merchant with a corresponding geolocation for a predefined amount of time.

FIG. **3** is a schematic diagram illustrating data **300** which may be stored in the database **316** of the messaging server system **108**, according to certain example embodiments. While the content of the database **316** is shown to comprise a number of tables, it will be appreciated that the data could be stored in other types of data structures (e.g., as an object-oriented database).

The database **316** includes message data stored within a message table **314**. An entity, table **302** stores entity data, including an entity graph **304**. Entities for which records are maintained within the entity table **302** may include individuals, corporate entities, organizations, objects, places, events, and so forth. Regardless of type, any entity regarding which the messaging server system **108** stores data may be a recognized entity. Each entity is provided with a unique identifier, as well as an entity type identifier (not shown).

The entity graph **304** furthermore stores information regarding relationships and associations between entities. Such relationships may be social, professional (e.g., work at a common corporation or organization) interested-based or activity-based, merely for example.

The database **316** also stores annotation data, in the example form of filters, in an annotation table **312**. Filters for which data is stored within the annotation table **312** are associated with and applied to videos (for which data is stored in a video table **310**) and/or images (for which data is stored in an image table **308**). Filters, in one example, are overlays that are displayed as overlaid on an image or video during presentation to a recipient user. Filters may be of various types, including user-selected filters from a gallery of filters presented to a sending user by the messaging client application **104** when the sending user is composing a message. Other types of filers include geolocation filters (also known as geo-filters) which may be presented to a sending user based on geographic location. For example, geolocation filters specific to a neighborhood or special location may be presented within a user interface by the messaging client application **104**, based on geolocation information determined by a global positioning system (GPS) unit of the client device **102**. Another type of filer is a data filer, which may be selectively presented to a sending user by the messaging client application **104**, based on other inputs or information gathered by the client device **102** during the message creation process. Examples of data filters include current temperature at a specific location, a current speed at which a sending user is traveling, battery life for a client device **102** or the current time.

Other annotation data that may be stored within the image table **308** is so-called "lens" data. A "lens" may be a real-time special effect and sound that may be added to an image or a video.

As mentioned above, the video table **310** stores video data which, in one embodiment, is associated with messages for which records are maintained within the message table **314**. Similarly, the image table **308** stores image data associated with messages for which message data is stored in the entity table **302**. The entity table **302** may associate various annotations from the annotation table **312** with various images and videos stored in the image table **308** and the video table **310**.

A story table **306** stores data regarding collections of messages and associated image, video or audio data, which are compiled into a collection (e.g., a story or a gallery). The creation of a particular collection may be initiated by a particular user (e.g., each user for which a record is maintained in the entity table **302**) A user may create a "personal story" in the form of a collection of content that has been created and sent/broadcast by that user. To this end, the user interface of the messaging client application **104** may include an icon that is user selectable to enable a sending user to add specific content to his or her personal story.

A collection may also constitute a "live story," which is a collection of content from multiple users that is created manually, automatically or using a combination of manual and automatic techniques. For example, a "live story" may constitute a created stream of user-submitted content from varies locations and events. Users, whose client devices have location services enabled and are at a common location event at a particular time may, for example, be presented with an option, via a user interface of the messaging client application **104**, to contribute content to a particular live story. The live story may be identified to the user by the messaging client application **104**, based on his or her location. The end result is a "live story" told from a community perspective.

A further type of content collection is known as a "location story", which enables a user whose client device **102** is located within a specific geographic location (e.g., on a college or university campus) to contribute to a particular collection. In some embodiments, a contribution to a location story may require a second degree of authentication to verify that the end user belongs to a specific organization or other entity (e.g., is a student on the university campus).

FIG. **4** is a schematic diagram illustrating a structure of a message **400**, according to some in some embodiments, generated by a messaging client application **104** for communication to a further messaging client application **104** or the messaging server application **114**. The content of a particular message **400** is used to populate the message table **314** stored within the database **120**, accessible by the messaging server application **114**. Similarly, the content of a message **400** is stored in memory as "in-transit" or "in-flight" data of the client device **102** or the application server **112**. The message **400** is shown to include the following components:

- A message identifier **402**: a unique identifier that identifies the message **400**.
- A message text payload **406**: text, to be generated by a user via a user interface of the client device **102** and that is included in the message **400**
- A message image payload **408**: image data, captured by a camera component of a client device **102** or retrieved from memory of a client device **102**, and that is included in the message **400**.
- A message video payload **412**: video data, captured by a camera component or retrieved from a memory component of the client device **102** and that is included in the message **400**.
- A message audio payload **416**: audio data, captured by a microphone or retrieved from the memory component of the client device **102**, and that is included in the message **400**.
- A message annotation **420**: annotation data (e.g., filters, stickers or other enhancements) that represents annotations to be applied to message image payload **408**, message video payload **412**, or message audio payload **416** of the message **400**.
- A message duration parameter **424**: parameter value indicating, in seconds, the amount of time for which content of the message (e.g., the message image payload **408**, message video payload **412**, message audio payload **416**) is to be presented or made accessible to a user via the messaging client application **104** (deleted).
- A message geolocation parameter **426**: geolocation data (e.g., latitudinal and longitudinal coordinates) associated with the content payload of the message. Multiple message geolocation parameter **426** values may be included in the payload, each of these parameter values being associated with respect to content items included in the content (e.g., a specific image into within the message image payload **408**, or a specific video in the message video payload **412**).
- A message story identifier **428**: identifier values identifying one or more content collections (e.g., "stories") with which a particular content item in the message image payload **408** of the message **400** is associated. For example, multiple images within the message image payload **408** may each be associated with multiple content collections using identifier values.
- A message tag **430**: each message **400** may be tagged with multiple tags, each of which is indicative of the subject matter of content included in the message payload. For example, where a particular image included in the message image payload **408** depicts an animal (e.g., a lion), a tag value may be included within the message tag **430** that is indicative of the relevant animal. Tag values may be generated manually, based on user input, or may be automatically generated using, for example, image recognition.
- A message sender identifier **432**: an identifier (e.g., a messaging system identifier, email address or device identifier) indicative of a user of the client device **102** on which the message **400** was generated and from which the message **400** was sent
- A message receiver identifier **434**: an identifier (e.g., a messaging system identifier, email address or device identifier) indicative of a user of the client device **102** to which the message **400** is addressed.

The contents (e.g. values) of the various components of message **400** may be pointers to locations in tables within which content data values are stored. For example, an image value in the message image payload **408** may be a pointer to (or address of) a location within an image table **414**. Similarly, values within the message video payload **412** may point to data stored within a video table **418**, values stored within the message annotations **420** may point to data stored in an annotation table **422**, values stored within the message story identifier **428** may point to data stored in a story table **410**, and values stored within the message sender identifier **432** and the message receiver identifier **434** may point to user records stored within an entity table **404**.

FIG. **5** is a schematic diagram illustrating an access-limiting process **500**, in terms of which access to content (e.g., an ephemeral message **502**, and associated multimedia payload of data) or a content collection (e.g., an ephemeral message story **506**) may be time-limited (e.g., made ephemeral).

An ephemeral message **502** is shown to be associated with a message duration parameter **508**, the value of which determines an amount of time that the ephemeral message

502 will be displayed to a receiving user of the ephemeral message 502 by the messaging client application 104. In one embodiment, an ephemeral message 502 is viewable by a receiving user for up to a maximum of 10 seconds, depending on the amount of time that the sending user specifies using the message duration parameter 508.

The message duration parameter 508 and the message receiver identifier 518 are shown to be inputs to a message timer 514, which is responsible for determining the amount of time that the ephemeral message 502 is shown to a particular receiving user identified by the message receiver identifier 518. In particular, the ephemeral message 502 will only be shown to the relevant receiving user for a time period determined by the value of the message duration parameter 508. The message timer 514 is shown to provide output to a more generalized ephemeral timer system 504, which is responsible for the overall timing of display of content (e.g., an ephemeral message 502) to a receiving user.

The ephemeral message 502 is shown in FIG. 5 to be included within an ephemeral message story 506 (e.g., a personal story, or an event story). The ephemeral message story 506 has an associated story duration parameter 510, a value of which determines a time-duration for which the ephemeral message story 506 is presented and accessible to users of the messaging system 100. The story duration parameter 510, for example, may be the duration of a music concert, where the ephemeral message story 506 is a collection of content pertaining to that concert. Alternatively, a user (either the owning user or a curator user) may specify the value for the story duration parameter 510 when performing the setup and creation of the ephemeral message story 506.

Additionally, each ephemeral message 502 within the ephemeral message story 506 has an associated story participation parameter 512, a value of which determines the duration of time for which the ephemeral message 502 will be accessible within the context of the ephemeral message story 506. Accordingly, a particular ephemeral message story 506 may "expire" and become inaccessible within the context of the ephemeral message story 506, prior to the ephemeral message story 506 itself expiring in terms of the story duration parameter 510. The story duration parameter 510, story participation parameter 512, and message receiver identifier 518 each provide input to a story timer 516, which operationally determines, firstly, whether a particular ephemeral message 502 of the ephemeral message story 506 will be displayed to a particular receiving user and, if so, for how long. Note that the ephemeral message story 506 is also aware of the identity of the particular receiving user as a result of the message receiver identifier 518.

Accordingly, the story timer 516 operationally controls the overall lifespan of an associated ephemeral message story 506, as well as an individual ephemeral message 502 included in the ephemeral message story 506. In one embodiment, each ephemeral message 502 within the ephemeral message story 506 remains viewable and accessible for a time-period specified by the story duration parameter 510. In a further embodiment, a certain ephemeral message 502 may expire, within the context of ephemeral message story 506, based on a story participation parameter 512, Note that a message duration parameter 508 may still determine the duration of time for which a particular ephemeral message 502 is displayed to a receiving user, even within the context of the ephemeral message story 506. Accordingly, the message duration parameter 508 determines the duration of time that a particular ephemeral message 502 is displayed to a receiving user, regardless of whether the receiving user is viewing that ephemeral message 502 inside or outside the context of an ephemeral message story 506.

The ephemeral timer 504 may furthermore operationally remove a particular ephemeral message 502 from the ephemeral message story 506 based on a determination that it has exceeded an associated story participation parameter 512. For example, when a sending user has established a story participation parameter 512 of 24 hours from posting, the ephemeral timer 504 will remove the relevant ephemeral message 502 from the ephemeral message story 506 after the specified 24 hours. The ephemeral timer 504 also operates to remove an ephemeral message story 506 either when the story participation parameter 512 for each and every ephemeral message 502 within the ephemeral message story 506 has expired, or when the ephemeral message story 506 itself has expired in terms of the story duration parameter 510.

In certain use cases, a creator of a particular ephemeral message story 506 may specify an indefinite story duration parameter 510. In this case, the expiration of the story participation parameter 512 for the last remaining ephemeral message 502 within the ephemeral message story 506 will determine when the ephemeral message story 506 itself expires. In this case, a new ephemeral message 502, added to the ephemeral message story 506, with a new story participation parameter 512, effectively extends the life of an ephemeral message story 506 to equal the value of the story participation parameter 512.

Responsive to the ephemeral timer 504 determining that an ephemeral message story 506 has expired (e.g., is no longer accessible), the ephemeral timer system 202 communicates with the messaging system 100 (and, for example, specifically the messaging client application 104 to cause an indicium (e.g., an icon) associated with the relevant ephemeral message story 506 to no longer be displayed within a user interface of the messaging client application 104. Similarly, when the ephemeral timer system 202 determines that the message duration parameter 508 for a particular ephemeral message 502 has expired, the ephemeral timer system 202 causes the messaging client application 104 to no longer display an indicium (e.g., an icon or textual identification) associated with the ephemeral message 502.

Turning now to the human pose tracking framework 124, the human pose tracking framework 124 uses convolutional neural networks (CNN). Features in a neural network are the variables or attributes in a data set that can be used as predictors by the CNN. FIG. 6 illustrates the feature-extraction process and classifier training 600, according to some example embodiments. Training the classifier may be divided into feature extraction layers 602 and classifier layer 614. Each image is analyzed in sequence by multiple layers 606-613 in the feature-extraction layers 602.

Feature extraction is a process to reduce the amount of resources required to describe a large set of data. When performing analysis of complex data, one of the problems stems from the number of variables involved. Analysis with a large number of variables generally requires a large amount of memory and computational power, and it may cause a classification algorithm to overfit to training samples and generalize poorly to new samples. Feature extraction is a general term describing methods of constructing combinations of variables to get around these large data-set problems while still describing the data with sufficient accuracy for the desired purpose.

Feature extraction may start from an initial set of measured data and builds derived values (features) intended to be informative and non-redundant, facilitating the subsequent learning and generalization steps. Further, feature extraction is related to dimensionality reduction, such as by reducing large vectors (sometimes with very sparse data) to smaller vectors capturing the same, or similar, amount of information.

Determining a subset of the initial features is called feature selection. The selected features are expected to contain the relevant information from the input data, so that the desired task can be performed by using this reduced representation instead of the complete initial data. Convolutional neural networks (CNN) use a stack of layers, where each layer performs a function. For example, the layer could be a convolution, a non-linear transform, the calculation of an average, etc. Eventually this convolutional neural network produces outputs by classifier layer **614**. In FIG. **6**, the data travels from left to right and the features are extracted. The goal of training the neural network is to find the parameters of all the layers that make them adequate for the desired task.

The structure of each layer may be predefined. For example, a convolution layer may contain small convolution kernels and their respective convolution parameters, and a summation layer may calculate the sum, or the weighted sum, of two pixels of the input image. Training assists in defining the weight coefficients for the summation.

Turning now to FIG. **7**, FIG. **7** is a block diagram illustrating a human pose tracking framework according to some example embodiments. The human pose tracking framework **124** receives video frames **702** as input and outputs pose estimation results **704** for each input frame. The pose estimation results **704** relate to the joint locations of the human across video frames.

The human pose tracking framework **124** tracks articulated body joints in monocular videos. In one example embodiment, the human pose tracking framework **124** is optimized by leveraging temporal information from the video frames **702** to compute pose estimation results **704**. The temporal information may improve accuracy for joint localization in frames and improve the consistency of joint localization across the frames. As a result, the temporal information improves the efficiency of a human pose tracking framework **124**.

FIG. **8** is a flowchart illustrating a method **800**, according to some example embodiments, to process video frames. While the method **800** is described within the context of a multimodal message and the messaging system **100**, the described operations could be performed with respect to video frames in other contexts.

At operation **802**, the human pose tracking framework **124** identifies a multimodal message comprising of video frames. The multimodal message may be in the form of an ephemeral message **502** or an ephemeral message story **506**.

At operation **900**, the human pose tracking framework **124** generates joint data representing multiple joint locations of a human in the video frames, using a composite convolutional neural network. In a convolutional neural network, the units within a hidden layer are divided into "feature maps." The following paragraphs use "feature maps" and "features" interchangeably.

To further expand upon operation **900**, references nominated to FIG. **9** and FIG. **10**. As shown in FIG. **10**, the human pose tracking framework **124** processes two sets of video frames. The first set of video frames includes an initial video frame (e.g., first frame **1002**). The second set of video frames includes subsequent video frames that appear after an initial video frame (e.g., second frame **1004**, third frame **1006**)

The human pose tracking framework **124** receives a first frame **1002** for which it has no temporal information. At operation **902**, the first frame **1002** is inputted into a "deep" convolutional neural network (e.g., "deep" CNN **1008**), The first frame **1002** is inputted into the "deep" CNN **1008** to initialize the pose tracking. The "deep" CNN **1008** extracts features from the first frame **1002** and inputs the features into a pose machine **1012**. Once the human pose tracking framework **124** has an initial pose estimation, the human pose tracking framework **124**, at operation **904**, extract features from each of subsequent second frame **1004** and subsequent third frame **1006** using a "shallow" CNN **1010**. In some example embodiment, a "deep" CNN **1008** may be used to extract features from the second frame **1004** or the third frame **1006**. In one example embodiment, the "deep" CNN **1008** includes additional deconvolution layers. These additional deconvolution layers may improve the performance of the human pose tracking framework **124** by upsampling the feature maps.

The "deep" CNN **1008** may consist of more convolutional layers than the "shallow" CNN **1010**. For example, the "deep" CNN **1008** may contain 50 layers, while the "shallow" CNN **1010** includes three convolution layers. In another example embodiment, "deep" CNN may contain at least five convolution layers.

Returning to FIG. **9**, at operation **906**, the human pose tracking framework **124** tracks multiple joint location using a one-shot learner neural network (e.g., one-shot model **1014**) based on a concatenation of feature maps and a convolutional pose machine **1012**. The convolutional pose machine **1012** is a pose machine implemented using a "shallow" convolutional neural network. Specifically, the pose machine **1012** consists of a convolutional pose machine. For a full explanation of convolutional pose machines refer to "Convolutional Pose Machines" by The Robotics Institute, Carnegie Mellon University. The pose machine **1012** receives the image features extracted by the "deep" CNN **1008** as input and outputs estimates of human skeleton coordinates. The image features extracted by the "deep" CNN **1008** may be fused with the estimates of human skeleton coordinates and subsequently, inputted into the one-shot model **1014**. Fusing the extracted image features and estimates of human skeleton coordinates may be beneficial in providing the human pose tracking framework **124** with initial pose estimation results **704**.

The one-shot model **1014** receives the fused "deep" CNN **1008** features and estimates of human skeleton coordinates as input, and directly outputs a template of key points to a correlation filter **1016** for pose tracking. The template of key points represents human skeleton coordinates of an image patch within the first frame **1002**. The one-shot model **1014** may be implemented using a convolutional neural network. The one-shot model **1014** can learn from one or only a few, training objects.

FIG. **11** is a diagrammatic representation of joint localization **1100** according to an example embodiment. Addition of the one-shot model **1014** in the human pose tracking framework **124** improves the human pose tracking framework **124** by achieving more accurate and stable pose estimation results **704**, as depicted in FIG. **11**. Unlike using an LSTM or a "shallow" CNN, the one-shot model **1014** is capable of propagating the long-range temporal information within the video frames **702**. Thus, with the one-shot model, **1014** the human pose tracking framework **124** may effectively leverage temporal information and improve the pose estimation results **704**.

An example formula for the correlation filter **1016** may be as follows:

$$\hat{G}_{k,l,m} = \sum_{i,j} \hat{K}_{i,j,m} \cdot F_{k+i-1,l+j-1,m}$$

In one example embodiment, the correlation filter **1016** may be used to track articulated body joints through rotations, occlusions or other appearance changes across video frames. The correlation filter **1016** may be trained from a single frame and dynamically adapted as the articulated body joints change across video frames. In another example embodiment, the correlation filter **1016** may receive the templates of the key points from the one-shot model **1014** and the second frame **1004** as input. The correlation filter **1016** may compute the correlation between the template of the previous frame, and the subsequent frame to produce updated pose estimation results **704**. This process may be recurrently and sequentially exploited by the human pose tracking framework **124** to the remaining frames in the video for human pose tracking.

Returning to FIG. **8** having completed a description of operation **900**, at operation **804**, the human pose tracking framework **124** stores the pose estimation results **704**. The pose estimation results **704** may be transmitted to the messaging client application **104**. At operation **806**, the human pose tracking framework **124** may transmit the pose estimation results **704**, as part of user interface data, for presentation as graphical data on a graphical user interface presented by the messaging client application **104**. The graphical data may for example be a rendition of the pose estimation results **704** that consist of alphanumeric characters or an image.

FIG. **12** is a diagrammatic illustration of graphical data **1200** according to an example embodiment. In one example embodiment, the graphical data is an image with a character icon **1204** of the human in the video frames **702**. In another example embodiment, the graphical data is presented as an image overlay. The graphical data may be transmitted as an ephemeral message **502** or an ephemeral message story **506**.

FIG. **13** is a block diagram **1300** illustrating a software architecture **1304**, which can be installed on any one or more of the devices described herein. The software architecture **1304** is supported by hardware such as a machine **1302** that includes processors **1320**, memory **1326**, and I/O components **1338**. In this example, the software architecture **1304** can be conceptualized as a stack of layers, where each layer provides a particular functionality. The software architecture **1304** includes layers such as an operating system **1312**, libraries **1310**, frameworks **1308**, and applications **1306**. Operationally, the applications **1306** invoke API calls **1350** through the software stack and receive messages **1352** in response to the API calls **1350**.

The operating system **1312** manages hardware resources and provides common services. The operating system **1312** includes, for example, a kernel **1314**, services **1316**, and drivers **1322**. The kernel **1314** acts as an abstraction layer between the hardware and the other software layers. For example, the kernel **1314** provides memory management, processor management (e.g., scheduling), component management, networking, and security settings, among other functionality. The services **1316** can provide other common services for the other software layers. The drivers **1322** are responsible for controlling or interfacing with the underlying hardware. For instance, the drivers **1322** can include display drivers, camera drivers, BLUETOOTH® or BLUETOOTH® Low Energy drivers, flash memory drivers, serial communication drivers (e.g., Universal Serial Bus (USB) drivers), WI-FI® drivers, audio drivers, power management drivers, and so forth.

The libraries **1310** provide a low-level common infrastructure used by the applications **1306**. The libraries **1310** can include system libraries **1318** (e.g., C standard library) that provide functions such as memory allocation functions, string manipulation functions, mathematic functions, and the like. In addition, the libraries **1310** can include API libraries **1324** such as media libraries (e.g., libraries to support presentation and manipulation of various media formats such as Moving Picture Experts Group-4 (MPEG4), Advanced Video Coding (H.264 or AVC), Moving Picture Experts Group Layer-3 (MP3), Advanced Audio Coding (AAC), Adaptive Multi-Rate (AMR) audio codec, Joint Photographic Experts Group (JPEG or JPG), or Portable Network Graphics (PNG)), graphics libraries (e.g., an OpenGL framework used to render in two dimensions (2D) and three dimensions (3D) in a graphic content on a display), database libraries (e.g., SQLite to provide various relational database functions), web libraries (e.g., WebKit to provide web browsing functionality), and the like. The libraries **1310** can also include a wide variety of other libraries **1328** to provide many other APIs to the applications **1306**.

The frameworks **1308** provide a high-level common infrastructure that is used by the applications **1306**. For example, the frameworks **1308** provide various graphical user interface (GUI) functions, high-level resource management, and high-level location services. The frameworks **1308** can provide a broad spectrum of other APIs that can be used by the applications **1306**, some of which may be specific to a particular operating system or platform.

In an example embodiment, the applications **1306** may include a home application **1336**, a contacts application **1330**, a browser application **1332**, a book reader application **1334**, a location application **1342**, a media application **1344**, a messaging application **1346**, a game application **1348**, and a broad assortment of other applications such as a third-party application **1340**. The applications **1306** are programs that execute functions defined in the programs. Various programming languages can be employed to create one or more of the applications **1306**, structured in a variety of manners, such as object-oriented programming languages (e.g., Objective-C, Java, or C++) or procedural programming languages (e.g., C or assembly language). In a specific example, the third-party application **1340** (e.g., an application developed using the ANDROID™ or IOS™ software development kit (SDK) by an entity other than the vendor of the particular platform) may be mobile software running on a mobile operating system such as IOS™, ANDROID™, WINDOWS® Phone, or another mobile operating system. In this example, the third-party application **1340** can invoke the API calls **1350** provided by the operating system **1312** to facilitate functionality described herein.

FIG. **14** is a diagrammatic representation of the machine **1400** within which instructions **1408** (e.g., software, a program, an application, an applet, an app, or other executable code) for causing the machine **1400** to perform any one or more of the methodologies discussed herein may be executed. For example, the instructions **1408** may cause the machine **1400** to execute any one or more of the methods described herein. The instructions **1408** transform the general, non-programmed machine **1400** into a particular machine **1400** programmed to carry out the described and illustrated functions in the manner described. The machine

1400 may operate as a standalone device or may be coupled (e.g., networked) to other machines. In a networked deployment, the machine 1400 may operate in the capacity of a server machine or a client machine in a server-client network environment, or as a peer machine in a peer-to-peer (or distributed) network environment. The machine 1400 may comprise, but not be limited to, a server computer, a client computer, a personal computer (PC), a tablet computer, a laptop computer, a netbook, a set-top box (STB), a PDA, an entertainment media system, a cellular telephone, a smartphone, a mobile device, a wearable device (e.g., a smartwatch), a smart home device (e.g., a smart appliance), other smart devices, a web appliance, a network router, a network switch, a network bridge, or any machine capable of executing the instructions 1408, sequentially or otherwise, that specify actions to be taken by the machine 1400. Further, while only a single machine 1400 is illustrated, the term "machine" shall also be taken to include a collection of machines that individually or jointly execute the instructions 1408 to perform any one or more of the methodologies discussed herein.

The machine 1400 may include processors 1402, memory 1404, and I/O components 1442, which may be configured to communicate with each other via a bus 1444. In an example embodiment, the processors 1402 (e.g., a Central Processing Unit (CPU), a Reduced Instruction Set Computing (RISC) processor, a Complex Instruction Set Computing (CISC) processor, a Graphics Processing Unit (GPU), a Digital Signal Processor (DSP), an ASIC, a Radio-Frequency Integrated Circuit (RFIC), another processor, or any suitable combination thereof) may include, for example, a processor 1406 and a processor 1410 that execute the instructions 1408. The term "processor" is intended to include multi-core processors that may comprise two or more independent processors (sometimes referred to as "cores") that may execute instructions contemporaneously. Although FIG. 14 shows multiple processors 1402, the machine 1400 may include a single processor with a single core, a single processor with multiple cores (e.g., a multi-core processor), multiple processors with a single core, multiple processors with multiples cores, or any combination thereof.

The memory 1404 includes a main memory 1412, a static memory 1114, and a storage unit 1416, both accessible to the processors 1402 via the bus 1444. The main memory 1404, the static memory 1414, and storage unit 1416 store the instructions 1408 embodying any one or more of the methodologies or functions described herein. The instructions 1408 may also reside, completely or partially, within the main memory 1412, within the static memory 1414, within machine-readable medium 1418 within the storage unit 1416, within at least one of the processors 1402 (e.g., within the processor's cache memory), or any suitable combination thereof, during execution thereof by the machine 1400.

Furthermore, the machine-readable medium is a tangible non-transitory machine—readable medium in that it does not embody a propagating signal. However, labeling the tangible machine-readable medium "non-transitory" should not be construed to mean that the medium is incapable of movement—the medium should be considered as being transportable from one real-world location to another. Additionally, since the machine-readable medium is tangible, the medium may be considered to be a machine-readable device.

The I/O components 1442 may include a wide variety of components to receive input, provide output, produce output, transmit information, exchange information, capture measurements, and so on. The specific I/O components 1442 that are included in a particular machine will depend on the type of machine. For example, portable machines such as mobile phones may include a touch input device or other such input mechanisms, while a headless server machine will likely not include such a touch input device. It will be appreciated that the I/O components 1442 may include many other components that are not shown in FIG. 14. In various example embodiments, the I/O components 1442 may include output components 1428 and input components 1430. The output components 1428 may include visual components (e.g., a display such as a plasma display panel (PDP), a light emitting diode (LED) display, a liquid crystal display (LCD), a projector, or a cathode ray tube (CRT)), acoustic components (e.g., speakers), haptic components (e.g., a vibratory motor, resistance mechanisms), other signal generators, and so forth. The input components 1430 may include alphanumeric input components (e.g., a keyboard, a touch screen configured to receive alphanumeric input, a photo-optical keyboard, or other alphanumeric input components), point-based input components (e.g., a mouse, a touchpad, a trackball, a joystick, a motion sensor, or another pointing instrument), tactile input components (e.g., a physical button, a touch screen that provides location and/or force of touches or touch gestures, or other tactile input components audio input components (e.g., a microphone), and the like.

In further example embodiments, the I/O components 1442 may include biometric components 1432, motion components 1434, environmental components 1436, or position components 1438, among a wide array of other components. For example, the biometric components 1432 include components to detect expressions (e.g., hand expressions, facial expressions, vocal expressions, body gestures, or eye tracking), measure biosignals (e.g., blood pressure, heart rate, body temperature, perspiration, or brain waves), identify a person (e.g., voice identification, retinal identification, facial identification, fingerprint identification, or electroencephalogram-based identification), and the like. The motion components 1434 include acceleration sensor components (e.g., accelerometer), gravitation sensor components, rotation sensor components (e.g., gyroscope), and so forth. The environmental components 1436 include, for example, illumination sensor components (e.g., photometer), temperature sensor components (e.g., one or more thermometers that detect ambient temperature), humidity sensor components, pressure sensor components (e.g., barometer), acoustic sensor components (e.g., one or more microphones that detect background noise), proximity sensor components (e.g., infrared sensors that detect nearby objects), gas sensors (e.g., gas detection sensors to detection concentrations of hazardous gases for safety or to measure pollutants in the atmosphere), or other components that may provide indications, measurements, or signals corresponding to a surrounding physical environment. The position components 1438 include location sensor components (e.g., a GPS receiver component), altitude sensor components (e.g., altimeters or barometers that detect air pressure from which altitude may be derived), orientation sensor components (e.g., magnetometers), and the like.

Communication may be implemented using a wide variety of technologies. The I/O components 1442 further include communication components 1440 operable to couple the machine 1400 to a network 1420 or devices 1422 via a coupling 1424 and a coupling 1426, respectively. For example, the communication components 1440 may include a network interface component or another suitable device to interface with the network 1420, In further examples, the communication components 1440 may include wired communication components, wireless communication components, cellular communication components, Near Field Communication (NFC) components, Bluetooth® components (e.g., Bluetooth® Low Energy), Wi-Fi® components, and other communication components to provide communication via other modalities. The devices 1422 may be another machine or any of a wide variety of peripheral devices, a peripheral device coupled via a USB).

Moreover, the communication components 1440 may detect identifiers or include components operable to detect identifiers. For example, the communication components 1440 may include Radio Frequency identification (MD) tag reader components, NFC smart tag detection components, optical reader components (e.g., an optical sensor to detect one-dimensional barcodes such as Universal Product Code (UPC) bar code, multi-dimensional bar codes such as Quick Response (QR) code, Aztec code, Data Matrix, Dataglyph, MaxiCode, PDF417, Ultra Code, UCC RSS-2D barcode, and other optical codes), or acoustic detection components (e.g., microphones to identify tagged audio signals). In addition, a variety of information may be derived via the communication components 1440, such as location via Internet Protocol (IP) geolocati on, location via Wi-Fi® signal triangulation, location via detecting an NFC beacon signal that may indicate a particular location, and so forth.

The various memories (e.g., memory 1404, main memory 1412, static memory 1414, and/or memory of the processors 1402) and/or storage unit 1416 may store one or more sets of instructions and data structures (e.g., software) embodying or used by any one or more of the methodologies or functions described herein. These instructions (e.g., the instructions 1408), when executed by processors 1402, cause various operations to implement the disclosed embodiments.

The instructions 1408 may be transmitted or received over the network 1420, using a transmission medium, via a network interface device (e.g., a network interface component included in the communication components 1440) and using any one of a number of well-known transfer protocols (e.g., hypertext transfer protocol (HTTP)). Similarly, the instructions 1408 may be transmitted or received using a transmission medium via the coupling 1426 (e.g., a peer-to-peer coupling) to the devices 1422

What is claimed is:

1. A method comprising:

identifying, using one or more processors, a multimodal message comprising a plurality of video frames, the plurality of video frames comprising a first set of video frames and a second set of video frames;

generating, using a composite convolutional neural network, joint data representing a plurality of joint locations of a human depicted in the plurality of video frames, the generating of the joint data by the composite convolutional neural network comprising:

operating on the first set of video frames using a deep convolutional neural network;

operating on the second set of video frames using a shallow convolutional neural network; and

tracking the plurality of joint locations using a one-shot learner neural network that is trained to track the plurality of joint locations based on a concatenation of:

feature maps comprising temporal information corresponding to the plurality of video frames; and

a convolutional pose machine trained to produce pose estimation results corresponding to the plurality of joint locations in the plurality of video frames;

generating, based on the concatenating, a template of key points representing the plurality of joint locations;

generating updated pose estimation results using a correlation filter trained to compute a correlation between the first set of video frames and the second set of video frames using the template of key points and the second set of video frames;

storing, using the one or more processors, the updated pose estimation results of the human depicted in the plurality of video frames; and

causing presentation of a rendition of the updated pose estimation results of the human on a user interface of a client device.

2. The method of claim 1 wherein the feature maps are produced by the deep convolutional neural network and the shallow convolutional neural network.

3. The method of claim 1 wherein the first set of video frames comprises an initial video frame and the second set of video frames comprises subsequent video frames which follow the initial video frame.

4. The method of claim 1 wherein a number of layers in the deep convolutional neural network is at least five.

5. The method of claim 1 wherein the one-shot learner neural network directly outputs the template of key points.

6. The method of claim 5 wherein the one-shot learner neural network outputs the template of key points to the correlation filter.

7. The method of claim 1, wherein the rendition is a character icon of the human in the plurality of video frames.

8. A system comprising:

a processor; and

a memory storing instructions that, when executed by the processor, configure the system to perform operations comprising:

identifying a multimodal message comprising a plurality of video frames, the plurality of video frames comprising a first set of video frames and a second set of video frames;

generating, using a composite convolutional neural network, joint data representing a plurality of joint locations of a human depicted in the plurality of video frames, the generating of the joint data by the composite convolutional neural network comprising:

operating on the first set of video frames using a deep convolutional neural network;

operating on the second set of video frames using a shallow convolutional neural network; and

tracking the plurality of joint locations using a one-shot learner neural network that is trained to track the plurality of joint locations based on a concatenation of:

feature maps comprising temporal information corresponding to the plurality of video frames; and

a convolutional pose machine trained to produce pose estimation results corresponding to the plurality of joint locations in the plurality of video frames;

generating, based on the concatenating, a template of key points representing the plurality of joint locations;

generating updated pose estimation results using a correlation filter trained to compute a correlation between the first set of video frames and the second set of video frames using the template of key points and the second set of video frames;

storing the updated pose estimation results of the human depicted in the plurality of video frames; and

causing presentation of a rendition of the updated pose estimation results of the human on a user interface of a client device.

**9**. The system of claim **8** wherein the feature maps are produced by the deep convolutional neural network and the shallow convolutional network.

**10**. The system of claim **8** wherein the first set of video frames comprises an initial video frame and the second set of video frames comprises subsequent video frames which follow the initial video frame.

**11**. The system of claim **8** wherein a number of layers in the deep convolutional neural network is at least five.

**12**. The system of claim **8** wherein the deep convolutional neural network contains at least one deconvolution layer.

**13**. The system of claim **8** wherein the one-shot learner neural network directly outputs a plurality of correlation filters.

**14**. The system of claim **8**, wherein the rendition is a character icon of a user associated with the client device.

**15**. A non-transitory computer-readable storage medium, the computer-readable storage medium including instructions that when executed by a computer, cause the computer to perform operations comprising:

identifying a multimodal message comprising a plurality of video frames, the plurality of video frames comprising a first set of video frames and a second set of video frames;

generating, using a composite convolutional neural network, joint data representing a plurality of joint locations of a human depicted in the plurality of video frames, the generating of the joint data by the composite convolutional neural network comprising:

operating on the first set of video frames using a deep convolutional neural network;

operating on the second set of video frames using a shallow convolutional neural network; and

tracking the plurality of joint locations using a one-shot learner neural network that is trained to track the plurality of joint locations based on a concatenation of:

feature maps comprising temporal information corresponding to the plurality of video frames; and

a convolutional pose machine trained to produce pose estimation results corresponding to the plurality of joint locations in the plurality of video frames;

generating, based on the concatenating, a template of key points representing the plurality of joint locations;

generating updated pose estimation results using a correlation filter trained to compute a correlation between the first set of video frames and the second set of video frames using the template of key points and the second set of video frames;

storing the updated pose estimation results of the human depicted in the plurality of video frames; and

causing presentation of a rendition of the updated pose estimation results of the human on a user interface of a client device.

**16**. The non-transitory computer-readable storage medium of claim **15** wherein the feature maps are produced by the deep convolutional neural network and the shallow convolutional network.

**17**. The non-transitory computer-readable storage medium of claim **15** wherein the first set of video frames comprises an initial video frame and the second set of video frames comprises subsequent video frames which follow the initial video frame.

**18**. The non-transitory computer-readable storage medium of claim **15** wherein a number of layers in the deep convolutional neural network is at least five.

**19**. The non-transitory computer-readable storage medium of claim **15** wherein the deep convolutional neural network contains at least one deconvolution layer.

**20**. The non-transitory computer-readable storage medium of claim **15** wherein the one-shot learner neural network directly outputs a plurality of correlation filters.

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